## Projection Based Model Order Reduction for Multiphysical Problems

## Short Course Part 2 - I | Vector

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## Agenda

## Discrete Fourier Transformation



Discrete Fourier Transformation and Vector Space


Link to Model Order Reduction


How to find a good Subspace

## How to find a good Subspace

Modal Analysis

## How to find a good Subspace

CADFEm
Krylov Subspace - Implicit Krylov Subspace
Moment Matching

How to find a good Subspace
-FULL
Based on Simulation Results
How to find a good Subspace

Gram Schmidt Orthogonalization

How to find a good Subspace


## Discrete Fourier Transformation

...is some kind of model order reduction


Discrete Fourier Transformation

## Starting point

- Continuous series $y(x) \in \mathbb{R}^{\infty}$ $\rightarrow$ Infinite number of points



## Discrete Fourier Transformation

## Discretization

## Starting point

- Continuous series $y(x) \in \mathbb{R}^{\infty}$
$\rightarrow$ Infinite number of points


## Discretized

- $\mathbf{y}=\left\{y_{0}, \ldots, y_{\mathrm{N}-1}\right\} y \in \mathbb{R}^{N}$
- $N$ Number of timepoints

$\rightarrow$ From infinite to $N$ ©


## Discrete Fourier Transformation




## Discrete Fourier Transformation




## Discrete Fourier Transformation




## Discrete Fourier Transformation




## Discrete Fourier Transformation




## Discrete Fourier Transformation




## Discrete Fourier Transformation




## Discrete Fourier Transformation

## Fourier Coefficients

- $\hat{y}_{k}=\sum_{j=0}^{N-i} \mathrm{e}^{-2 \pi \mathrm{i} \frac{\mathrm{i}}{N}} y_{j}$
- for $k=0, \ldots N-1$


## In Matrix Notation

- $\hat{\mathbf{y}}=\boldsymbol{\Phi}^{\mathrm{T}} \mathbf{y}$
- with $\boldsymbol{\Phi}[j, k]=\mathrm{e}^{-2 \pi \frac{j}{\mathrm{j}} \frac{k}{N}}$


## Discrete Fourier Transformation

## Inverse Discrete

Fourier Transformation

- $y_{k}=\frac{1}{N} \sum_{j=0}^{N-i} \mathrm{e}^{2 \pi \mathrm{i} \frac{j k}{N}} \hat{y}_{j}$
- for $k=0, \ldots N-1$


## In Matrix Notation

- $\mathbf{y}=\left[\boldsymbol{\Phi}^{\mathrm{T}}\right]^{-1} \hat{\mathbf{y}}$
- with $\boldsymbol{\Phi}[j, k]=\mathrm{e}^{-2 \pi \mathrm{i} \frac{j k}{N}}$



## Discrete Fourier Transformation

## Link to model order reduction?

## Discretized signal

- $y=\left\{y_{0}, \ldots, y_{N-1}\right\} y \in \mathbb{R}^{N}$, Order $N$

Representation by DFT

- $\hat{y}_{k}=\sum_{j=0}^{N-i} \mathrm{e}^{-2 \pi \frac{\mathrm{i} k}{N}} y_{j}, \hat{y} \in \mathbb{R}^{N}$, Order $N$
- for $k=0, \ldots N-1$


The same data is represented

- ...but in different coordinates
- They can be interpretated in a different way

Let's call $\hat{y}$ generalized coordinates


Discrete Fourier Transformation
...is some kind of model order reduction

## Reduce Dimension

- By taking less Fourier coefficients
- Error is introduced


## Vector Space

## EuroSime

## CADFEm

Ansys<br>CHANNEL PARTNER



## Vector Space V

Vector a


Mathematician

- A vector in $\mathbb{R}^{2}$


## Vector Space V

## Basis of Vector Space

## Basis B

- ... of a vector space $\mathbf{V}$ with basis vectors $\mathbf{b}_{1}$ to $\mathbf{b}_{m}$
- $\mathbf{B}=\left[\mathbf{b}_{1}, \ldots, \mathbf{b}_{m}\right] \in \mathbb{R}^{m}$
- $m$ is the dimension of the vector space

Those basis vectors must be linear independent

- Each vector can be represented as a linear combination of basis vectors and this representation is unique
- Euclidian basis $\mathbb{R}^{m}$ (also called standard, natural or canonical basis)
- $\mathbf{b}_{1}=\left\{\begin{array}{l}1 \\ 0\end{array}\right\}, \mathbf{b}_{2}=\left\{\begin{array}{l}0 \\ 1\end{array}\right\}$
- $\mathbf{B}_{1}=\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]=\mathbf{I}$

Vector Space V
Basis of Vector Space
FEM

- "1" at one node, all others are 0
- $\in \mathbb{R}^{N}$
- $N$ is the number of dofs



## Vector Space V

## Coordinates of a vector

## Vector a

- ... with its coordinates $a_{1}$ to $a_{N}$ with respect to basis $\mathbf{B}_{1}$
$\cdot \mathbf{a}=\left\{a_{1}, \ldots, a_{N}\right\} \quad \in \mathbb{R}^{N}$
- E.g. $\mathbf{a}=\left\{\begin{array}{l}2 \\ 1\end{array}\right\}$
- $2\left\{\begin{array}{l}1 \\ 0\end{array}\right\}+1\left\{\begin{array}{l}0 \\ 1\end{array}\right\}=\mathbf{B}_{1} \mathbf{a}=\left\{\begin{array}{l}2 \\ 1\end{array}\right\}$

Each vector can be represented

- ...as a linear combination of basis vectors
- and this representation is unique

In reduced order modeling

- Ba is called Expansion


## Vector Space V

Coordinates of a vector


## Vector Space V

The basis is not unique!

## Different basis

-E.g. $\mathbf{b}_{3}=\left\{\begin{array}{c}\frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2}\end{array}\right\}, \mathbf{b}_{4}=\left\{\begin{array}{c}\frac{-\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2}\end{array}\right\}$
$\cdot \mathbf{B}_{2}=\left[\begin{array}{cc}\frac{\sqrt{2}}{2} & \frac{-\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2}\end{array}\right]$
-spans the same vector space

## Vector

$\cdot \ldots$ with its coordinates $\hat{a}_{1}$ to $\hat{a}_{N}$ with respect to basis $\mathbf{B}_{2}$

- $\widehat{a}=\left\{\begin{array}{c}2.12 \\ -0.71\end{array}\right\}$
$\cdot 2.12\left\{\begin{array}{l}\frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2}\end{array}\right\}+-0.71\left\{\begin{array}{c}-\frac{\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2}\end{array}\right\}=\mathbf{B}_{2} \widehat{\boldsymbol{a}}$


## Vector Space V

The basis is not unique!
 $\int_{0.041667 \text { Min }}^{0.041667 \text { Max }}$


## Vector Space V

The basis is not unique!


## Vector Space V

Truncated Basis

One can truncate the basis by neglecting some basis vectors

- $\mathbf{B}_{1}=\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]$
- E.g. $\mathbf{B}_{1_{1}}=\left[\begin{array}{l}1 \\ 0\end{array}\right]$ or $\mathbf{B}_{1_{2}}=\left[\begin{array}{l}0 \\ 1\end{array}\right]$

The truncated basis spans a subspace of $\mathbf{V}$

## Vector Space V

Truncated Basis



## Vector Space V

## Truncated Basis

Error due to truncated basis


## Vector Space V

Scalar product / Inner Product

## Scalar Product

- Mathematical relationship that assigns a scalar to two vectors
- Often denoted as by $\langle\mathbf{a}, \mathbf{c}\rangle$
- $\langle\mathbf{a}, \mathbf{c}\rangle=\mathbf{a}^{\mathrm{T}} \mathbf{c}=$ $\sum_{j=1}^{N} a_{j} c_{j}=a_{1} c_{1}+\cdots+a_{N} c_{N}$
- E.g. $\mathbf{a}=\left\{\begin{array}{l}2 \\ 1\end{array}\right\}, \mathbf{c}=\left\{\begin{array}{l}0 \\ 1\end{array}\right\}$

- $\mathbf{a}^{\mathrm{T}} \mathbf{c}=2 \cdot 0+1 \cdot 1=1$


# Vector Space V 

Scalar product / Inner Product

## Geometric interpretation in $\mathbb{R}^{2}$

- $\mathbf{a}^{\mathrm{T}} \mathbf{c}=\|\mathbf{a}\|\|\mathbf{c}\| \cos (\phi)$
- $\phi=\arccos \left(\frac{\mathbf{a}^{\mathrm{T}} \mathbf{c}}{\|\mathbf{a}\|\|\mathbf{c}\|}\right)$
- E.g. $\mathbf{a}=\left\{\begin{array}{l}2 \\ 1\end{array}\right\}, \mathbf{c}=\left\{\begin{array}{l}0 \\ 1\end{array}\right\}$
- $\phi=\arccos \left(\frac{2 \cdot 0+1 \cdot 1}{\sqrt{5} \cdot 1}\right)=63^{\circ}$



## Vector Space V

Orthogonality

## Two vectors are orthogonal if the scalar product is 0

- In $\mathbb{R}^{2}$ the angle is $90^{\circ}$
- E.g. $\mathbf{a}=\left\{\begin{array}{l}2 \\ 0\end{array}\right\}, \mathbf{c}=\left\{\begin{array}{l}0 \\ 1\end{array}\right\}$
- $\mathbf{a}^{\mathrm{T}} \mathbf{c}=2 \cdot 0+0 \cdot 1=0$



## Vector Space V

## Orthogonal Basis

## Orthogonal basis

- The scalar product is 0 for $\mathbf{b}_{i}^{T} \mathbf{b}_{j}$ with $i \neq j$
$\bullet=\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]=\left[\begin{array}{ll}1 \cdot 1+0 \cdot 0 & 1 \cdot 0+0 \cdot 0 \\ 0 \cdot 1+1 \cdot 0 & 0 \cdot 0+1 \cdot 1\end{array}\right]=\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]$


## $\mathbf{B}_{2}^{T} \mathbf{B}_{2}$

- 


## Vector Space V

## Orthogonal Projection

```
Given vector
```

$\cdot \mathbf{a}=\left\{\begin{array}{l}2 \\ 1\end{array}\right\}$

w.r.t to basis $\mathbf{B}_{1}$

- $\mathbf{B}_{1}=\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]$
- $\mathbf{B}_{1} \mathbf{a}=2\left\{\begin{array}{l}1 \\ 0\end{array}\right\}+1\left\{\begin{array}{l}0 \\ 1\end{array}\right\}$

Projection onto truncated basis $\mathbf{B}_{1_{1}}=\left[\begin{array}{l}1 \\ 0\end{array}\right]$
$\cdot \hat{a}_{1}=\mathbf{B}_{1_{1}}^{\mathrm{T}} \mathbf{a}=\left[\begin{array}{ll}1 & 0\end{array}\right]\left\{\begin{array}{l}2 \\ 1\end{array}\right\}=2$


Projection onto truncated basis $\mathrm{B}_{1_{2}}=\left[\begin{array}{l}0 \\ 1\end{array}\right]$
$\cdot \hat{a}_{2}=\mathbf{B}_{1_{2}}^{\mathrm{T}} \mathbf{a}=\left[\begin{array}{ll}0 & 1\end{array}\right]\left\{\begin{array}{l}2 \\ 1\end{array}\right\}=1$


## Vector Space V

## Change of Basis

## Change of basis of vector a

- $\mathbf{a}=\left\{\begin{array}{l}2 \\ 1\end{array}\right\}$
- From $\mathbf{B}_{1}=\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]$ to $\mathbf{B}_{\mathbf{2}}=\left[\begin{array}{cc}\frac{\sqrt{2}}{2} & \frac{-\sqrt{2}}{2} \\ \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2}\end{array}\right]$


Linear system of equations

- $\mathrm{B}_{1} \mathrm{a}=\mathrm{B}_{2}$ â


## Solution

- $\hat{a}=B_{2}^{-1} B_{1} \mathbf{a}$


## Vector Space V

Change of Basis - Why are orthogonal bases that nice?

## Solution

- $\hat{\mathrm{a}}=\mathrm{B}_{2}^{-1} \mathrm{~B}_{1} \mathbf{a}$

Why are orthogonal bases that nice?


- $\mathbf{B}_{2}^{-1}=\mathbf{B}_{2}^{\mathrm{T}}$
- $\hat{a}=B_{2}^{\mathrm{T}} \mathbf{B}_{1} \mathrm{a}$
- $\hat{a}=\left[\begin{array}{cc}\frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} \\ \frac{-\sqrt{2}}{2} & \frac{\sqrt{2}}{2}\end{array}\right]\left[\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right]\left\{\begin{array}{l}2 \\ 1\end{array}\right\}=\left\{\begin{array}{l}2.12 \\ -.71\end{array}\right\}$


## Vector Space V

Change of Basis - Projection

$$
\hat{\mathrm{a}}=\mathbf{B}_{2}^{\mathrm{T}} \mathbf{B}_{1} \mathrm{a}
$$

## In reduced order modeling



- If not denoted differently, the basis $\mathbf{B}_{1}$ is the Euclidian basis
- $\hat{\mathbf{a}}=\boldsymbol{\Phi}^{\mathrm{T}} \mathbf{a}$ is just called Projection
- The truncated basis is written as $\boldsymbol{\Phi}$, describing the subspace
- â are called generalized coordinates


## Vector Space V

## Norm

## Norm

- Assigns a non-negative real number to an element of the vector space
- Often denoted as $\|\cdot\|$.
- Generalization of the intuitive notion of "length" in the physical world

Often the norm is defined by the scalar
product

- $\|\mathbf{a}\|=\sqrt{\mathbf{a}^{\mathrm{T}} \mathbf{a}}$
- E.g. $\mathbf{a}=\left\{\begin{array}{l}2 \\ 1\end{array}\right\}$
- $\|\mathrm{a}\|=\sqrt{2 \cdot 2+1 \cdot 1}=\sqrt{5}$
-,L2-Norm", Euclidian norm



## Vector Space V

Normalization of Basis Vectors - Normalized to 1

|  57.422 Max <br> 55.773  <br> -54.123  <br> - 52.474 <br> -50.825  <br> -49.175  <br> -47.526  <br> -45.877  <br>  44.227 <br> 42.578 Min  |
| :---: |
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## Vector Space V



## Vector Space V

## Engineers...



## Discrete Fourier Transformation and Vector Space

## EuroSime

CADFEM
/Ansys / channée Rapriner


## Discrete Fourier Transformation

...is some kind of model order reduction

## Discretized

- $\mathbf{y}=\left\{y_{0}, \ldots, y_{N-1}\right\} y \in$ $\mathbb{R}^{N}$
- $N$ Number of timepoints
$\rightarrow$ From infinite to $N$ ()



## Discrete Fourier Transformation

...is some kind of model order reduction

- Basis that we have intuitively assumed
- I

| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |



## Discrete Fourier Transformation

...is some kind of model order reduction



Discrete Fourier Transformation
...is some kind of model order reduction

## Discrete Fourier Transformation

- In matrix notation
- $\hat{\mathbf{y}}=\boldsymbol{\Phi}^{\mathrm{T}} \mathbf{y}$


## Projection!

Discrete Fourier Transformation
...is some kind of model order reduction

## Discrete Fourier Transformation <br> Transformation <br> 

- In matrix notation
- $\hat{\mathbf{y}}=\boldsymbol{\Phi}^{\mathrm{T}} \mathbf{y}$


## Projection!

- Change of basis
$\Phi$



# Discrete Fourier Transformation 

## Eurosime CADFEM

...is some kind of model order reduction

$$
\boldsymbol{\Phi}^{\mathrm{T}} \boldsymbol{\Phi}
$$

## The basis is orthonormal <br> ()

| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0

## Discrete Fourier Transformation

...is some kind of model order reduction

## Inverse Discrete <br> Fourier Transformation

- In matrix notation
- $\mathbf{y}=\left[\boldsymbol{\Phi}^{\mathrm{T}}\right]^{-1} \hat{\mathbf{y}}$
- $\left[\boldsymbol{\Phi}^{\mathrm{T}}\right]^{-1}=\left[\boldsymbol{\Phi}^{\mathrm{T}}\right]^{\mathrm{T}}=\boldsymbol{\Phi}$
- $\mathbf{y}=\boldsymbol{\Phi} \hat{\mathbf{y}}$


## Expansion!



## Discrete Fourier Transformation

...is some kind of model order reduction

Possibility to reduce the
dimension

- by taking less Fourier coefficients


## Projection

- to a truncated subspace


## Error

- often measured by the L2-Norm of
 the difference


## Link to Model Order Reduction

## PCB Model

## EuroSime

CADFEm


## Discretization



## PCB Model

## Vector Space

- Vector space of dimension
- Exemplary base vectors




## PCB Model

Describing Equations
$\mathbf{K u}=\mathbf{F}$, with external force vector $\mathbf{F}$


## PCB Model

## Solving

$$
\mathbf{K}^{-1} \mathbf{F}=\mathbf{u}
$$



## PCB Model

## Projection of Displacements

Project the displacements

- onto a smaller subspace of dimension $n \ll N$

$$
\mathbf{u}=\boldsymbol{\Phi}_{\mathbf{u}} \widehat{\mathbf{u}}+\mathbf{r}
$$

- As it is only an approximation, the residual $\mathbf{r}$ is introduced

$$
\mathbf{K} \mathbf{u}=\mathbf{F}
$$

- $K \Phi_{\mathbf{u}}(\widehat{\mathbf{u}}+\mathbf{r})=\mathbf{F}-\mathbf{K} \Phi_{\mathbf{u}} \mathbf{r}$
- $\boldsymbol{K} \Phi_{\mathbf{u}} \widehat{\mathbf{u}}=\mathbf{F}-\mathbf{K} \Phi_{\mathbf{u}} \mathbf{r}$

$$
\mathbf{K} \Phi_{\mathbf{u}} \widehat{\mathbf{u}}=\mathbf{F}-\tilde{\mathbf{r}}
$$



## PCB Model

Projection of Displacements

$$
\mathbf{K} \Phi_{\mathbf{u}} \widehat{\mathbf{u}}=\mathbf{F}-\tilde{\mathbf{r}}
$$



## Galerkin Condition

$$
\mathbf{K} \Phi_{\mathrm{u}} \widehat{\mathrm{u}}=\mathbf{F}-\tilde{\mathbf{r}}
$$

## Galerkin condition

- The residual $\tilde{\mathbf{r}}$ is kept orthogonal to the subspace $\boldsymbol{\Phi}_{\mathbf{u}}$

$$
\boldsymbol{\Phi}_{\mathbf{u}}^{\mathrm{T}} \tilde{\mathbf{r}}=\mathbf{0}
$$

- Multiply by $\boldsymbol{\Phi}_{\mathrm{u}}^{\mathrm{T}}$
- $\boldsymbol{\Phi}_{\mathbf{u}}^{T} \mathbf{K} \boldsymbol{\Phi}_{\mathbf{u}} \widehat{\mathbf{u}}=\boldsymbol{\Phi}_{\mathbf{u}}^{\mathrm{T}} \mathbf{F}-\boldsymbol{\Phi}_{\mathbf{u}}^{\mathrm{T}} \tilde{\mathbf{r}}$
- $\underbrace{\boldsymbol{\Phi}_{\mathbf{u}}^{\mathrm{T}} \mathbf{K} \boldsymbol{\Phi}_{\mathbf{u}} \widehat{\mathbf{u}}}_{\overparen{\mathbf{K}}}=\underbrace{\boldsymbol{\Phi}_{\mathbf{u}}^{\mathrm{T}} \mathbf{F}}_{\tilde{\mathbf{F}}}$


## PCB Model

Reduced Order Model

- $\boldsymbol{\Phi}_{\mathbf{u}}^{\mathrm{T}} \mathbf{K} \boldsymbol{\Phi}_{\mathbf{u}} \widehat{\mathbf{u}}=\boldsymbol{\Phi}_{\mathbf{u}}^{\mathrm{T}} \mathbf{F}$



## PCB Model

## Reduced Order Model

$\cdot \underbrace{\boldsymbol{\Phi}_{\mathbf{u}}^{\mathrm{T}} \mathbf{K} \boldsymbol{\Phi}_{\mathbf{u}}}_{\overparen{\mathbf{K}}} \widehat{\mathbf{u}}=\underbrace{\boldsymbol{\Phi}_{\mathbf{u}}^{\mathrm{T}} \mathbf{F}}_{\widehat{\mathbf{F}}}$


I

Reduced Order Model

## Generalized...

- stiffness matrix $\widehat{\mathbf{K}}$
- force vector $\hat{\mathbf{F}}$
- displacement vector $\widehat{u}$



## PCB Model

## Idea of Projection Based Model Order Reduction


https://www.facebook.com/examath/photos/a. 16610840
7455452/1180064439393172/?type=3

## How to find a good Subspace



## Based on System Matrices

- Modal Subspace
- Krylov Subspace


## Based on Simulation Results

- Gram Schmidt Orthogonalization
- Proper Orthogonal Decomposition/ Principal Component Analysis/ Method of Snapshots


## How to find a good Subspace

## Modal Analysis

## EuroSime

CADFEm
Ansys / chanelipx
HANNEL PARTNER


## Modal Analysis

## Eurosime CADFEII

"What the system wants to do" - Free Vibrations

## Equation of motion

- $\mathbf{M u ̈}+\mathbf{C u}+\mathbf{K u}=\mathbf{F}_{\text {ext }}$
- Damping is neglected
- Independent of external force


## $\rightarrow \mathrm{Mu}+\mathrm{Ku}=\mathbf{0}$

- Displacement vector $\mathbf{u} \in \mathbb{R}^{N}$
- Velocity vector
- Acceleration vector $\ddot{\mathbf{u}} \in \mathbb{R}^{N}$
- External Force
$\mathbf{F}_{\mathrm{ext}} \in \mathbb{R}^{N}$
- Mass Matrix
$\mathbf{M} \in \mathbb{R}^{N \times N}$
- Stiffness Matrix
$\mathbf{K} \in \mathbb{R}^{N \times N}$
- Damping Matrix


## Modal Analysis

"What the system wants to do" - Free Vibrations

> Equation of motion
> - $\mathbf{M u ̈}+\mathbf{C} \mathbf{u}+\mathbf{K u}=\mathbf{F}_{\text {ext }}$
> - Damping is neglected
> - Independent of external force

$$
\mathbf{M} \ddot{\mathbf{u}}+\mathbf{K} \mathbf{u}=\mathbf{0}
$$

For a linear system, free
vibrations are harmonic

- $\mathbf{u}=\boldsymbol{\Phi}_{i} \cos \omega_{i} t$
- Decomposition of $i-1-$ DOF-Oscillators
- $i^{\text {-th }}$ modeshape $\quad \boldsymbol{\Phi}_{i}$
- $i^{\text {-th }}$ natural frequency $\omega_{i}$
- Time $t$


## Modal Analysis

## "What the system wants to do" - Free Vibrations

$$
\mathbf{M} \ddot{\mathbf{u}}+\mathbf{K u}=\mathbf{0}
$$

- with $\ddot{\mathbf{u}}=-\omega^{2} \mathbf{u}$

$$
\left(-\omega^{2} \mathbf{M}+\mathbf{K}\right) \boldsymbol{\phi}_{i}=\mathbf{0}
$$

- This equation is satisfied if
- $\boldsymbol{\phi}_{i}=0$
- trivial, not of interest
- Determinant of $\left(-\omega^{2} \mathbf{M}+\mathbf{K}\right)$ is $\mathbf{0}$
(generalized) eigenvalue problem
- Outputs
- $n$ mode shapes $\boldsymbol{\Phi}=\left[\begin{array}{lll}\boldsymbol{\Phi}_{1} & \ldots & \boldsymbol{\Phi}_{n}\end{array}\right]$
- $n$ natural frequencies

$$
\boldsymbol{\omega}=\left\{\begin{array}{lll}
\omega_{1} & \ldots & \omega_{n}
\end{array}\right\}
$$

## Modal Analysis

"What the system wants to do" - Free Vibrations
Mode 1, $f_{1}=3.1 \mathrm{kHz}$
Mode 2, $f_{2}=4.3 \mathrm{kHz}$
Mode 3, $f_{3}=7.3 \mathrm{kHz}$


## Modal Analysis

## "What the system wants to do" - Free Vibrations

Implemented in all commercial FE-Codes

Number of mode shapes?
-The natural frequencies are ordered, from low to high frequencies

- In general: Dimension of the vector space of the model
$\rightarrow \rightarrow$ The same vector space is spanned
-Rule of thumb:
-Consider mode shapes up to twice the excitation frequency
$\rightarrow$ Modal Truncation


## Properties of mode shapes

- Orthogonal basis
- System matrices (K and $\mathbf{M}$ ) are decoupled
- Modal Superposition
-With "Mass normalization"
- $\boldsymbol{\Phi}^{\mathrm{T}} \mathbf{M} \boldsymbol{\Phi}=\operatorname{diag}(1)$, scalar product
- $\boldsymbol{\Phi}^{\mathrm{T}} \mathbf{K} \boldsymbol{\Phi}=\operatorname{diag}\left(\omega^{2}\right)$



## Modal Analysis

"What the system wants to do" - Free V

## Drawbacks

- Small structures $\rightarrow$ many modes
- Excitation is not considered
- Many inner modes
- Only for linear dynamics
- Commonly used for structural



## How to find a good Subspace

Krylov Subspace - Implicit Moment Matching


## Krylov Subspace

General definition of Krylov Subspace

- $\mathcal{K}=\mathcal{K}(\mathbf{A}, \mathbf{q})=\operatorname{span}\left\{\mathbf{q}, \mathbf{A q}, \ldots, \mathbf{A}^{m-1} \mathbf{q}\right\}$

Used in many algorithms

- Arnoldi (solution of eigenvalue problems)
- Lanczos (solution of eigenvalue problems)
- GMRES (approximate solution of systems of linear equations)
- QMR (approximate solution of systems of linear equations)
- . . -


## Moment Matching

What is a Moment in this Context?

## General transfer function

- in Laplace domain
- Fourier integral is a special case with $s=\mathrm{i} \omega$
- $\left(s^{2} \mathbf{M}-\mathbf{K}\right) \mathbf{u}=\mathbf{F}_{\mathrm{ext}}$

- $\underbrace{}_{\mathbf{K}_{\mathrm{eq}_{(s)}}^{\left(s^{2} \mathbf{M}-\mathbf{K}\right)}}{ }^{\mathbf{- 1}} \mathbf{F}_{\mathbf{e x t}}=\mathbf{u}$


## Moment Matching

What is a Moment in this Context?

$$
\underbrace{\left(s^{2} \mathbf{M}-\mathbf{K}\right)}_{\mathbf{K}_{\mathrm{eq}}^{(s)}}{ }^{-1} \mathbf{F}_{\mathrm{ext}}=\mathbf{u}
$$

## Taylor series

- around $s_{0}^{2}$
- $\mathbf{u}=\sum_{i} \mathbf{m}_{i}\left(s^{2}-s_{0}^{2}\right)^{i}$
- Hint: the $i$-th derivative in the Laplace
 domain is just $s^{i} \cdot f(s)$
- $\mathbf{m}_{i}$ are called moments of the transfer function


## Moment Matching

## Explicit Moment Matching

$$
\mathbf{u}=\sum_{i} \mathbf{m}_{i}\left(s^{2}-s_{0}^{2}\right)^{i}
$$

## Explicit calculation of moments

 is numerically unstable- $\mathbf{m}_{i}=\widetilde{\mathbf{M}}^{i} \tilde{\mathbf{F}}$
- $\widetilde{\mathbf{M}}^{i}=\left[-\mathbf{K}_{\text {eq }}^{\left(\mathbf{S}_{0}\right)}-\mathbf{M}\right]^{i}$
- $\widetilde{\mathbf{F}}=\mathbf{K}_{\text {eq }}^{\left(s_{0}\right)}{ }^{-1} \mathbf{F}_{\text {ext }}$



## Moment Matching

## Implicit Moment Matching

## Explicit Moments

- $\mathbf{m}_{i}=\widetilde{\mathbf{M}}^{i} \tilde{\mathbf{F}}$
- $\widetilde{\mathbf{M}}^{i}=\left[-\mathbf{K}_{\mathrm{eq}}^{\left(\mathbf{S}_{0}\right)}-1 \mathbf{M}\right]^{i}$
- $\tilde{\mathbf{F}}=\mathbf{K}_{\mathrm{eq}}^{\left({\left(0_{0}\right)}^{-1}\right.} \mathbf{F}_{\text {ext }}$


## Krylov subspace definition

- $\mathcal{K}=\mathcal{K}(\mathbf{A}, \mathbf{q})=\operatorname{span}\left\{\mathbf{q}, \mathbf{A q}, \ldots, \mathbf{A}^{m-1} \mathbf{q}\right\}$
- $\mathbf{A}=\widetilde{\mathbf{M}}$
- $\mathbf{q}=\tilde{\mathbf{F}}$


The moments lie in the Krylov Subspace!

- The first moment $\mathbf{q}$ is just the solution at the expansion point


## Moment Matching

## Implicit Moment Matching - Comments



## Moment Matching

## Implicit Moment Matching - Comments

Implicit moment matching is not limited to structural dynamics

Expansion point should be set according to the frequency range of interest

It is possible to use multiple expansion points

There is no established rule how many vectors should be considered

Can be expanded to "parametric model order reduction" the Taylor expansion is then done also for the parameter

## How to find a good Subspace

## Based on Simulation Results

## EuroSime

CADFEm


## Methods to Determine Subspaces

Based on Simulation Results

## Snapshot matrix

- Do a calculation for $m$ timesteps and assemble the results of interest $\mathbf{y} \mathbb{R}^{N}$ in a $\mathbf{S}=\left[\mathbf{y}_{1}, \ldots \mathbf{y}_{n}\right] \in \mathbb{R}^{N \times m}$

The snapshots define the vector space of the solution - how to find an orthonormal basis?

## How to find a good Subspace

## Gram Schmidt Orthogonalization



CADFEm

Insys<br>CHANNEL PARTNER



## Gram Schmidt Orthogonalization

## Given

- $m$ vectors $\mathbf{v}_{i}$ in $\mathbb{R}^{N}$


## Target

- $m$ orthonormal vectors $\mathbf{u}_{i}$ in $\mathbb{R}^{N}$

| Algorithm |  |
| :---: | :---: |
| $\cdot \mathbf{u}_{1}=\frac{\mathbf{v}_{1}}{\left\\|\mathbf{v}_{1}\right\\|}$ | Normalization of vector $\mathbf{v}_{1}$ |
| - $\mathbf{u}_{2}^{\prime}=\mathbf{v}_{2}-\frac{\left\langle\mathbf{v}^{2}, \mathbf{v}^{\prime} \mathbf{u}_{1}\right\rangle}{\left\langle\mathbf{u}_{1}, \mathbf{u}_{1}\right\rangle} \mathbf{u}_{1}$ | Orthogonalization of $\mathbf{v}_{2}$ |
| $\cdot \mathbf{u}_{2}=\frac{\mathbf{u}_{2}}{\left\\|\mathbf{u}^{\prime}\right\\|}$ | Normalization of vector $\mathbf{u}_{2}^{\prime}$ |
| $\bullet \mathbf{u}_{3}^{\prime}=\mathbf{v}_{3}-\frac{\left\langle\mathbf{v}_{3}, \mathbf{u}_{1}\right\rangle}{\left\langle\mathbf{u}_{1} \mathbf{u}_{1}\right\rangle} \mathbf{u}_{1}-\frac{\left\langle\mathbf{v}_{3}, \mathbf{u}_{2}\right\rangle}{\left\langle\mathbf{u}_{2}, \mathbf{u}_{2}\right\rangle} \mathbf{u}_{2}$ | Orthogonalization of $\mathbf{v}_{3}$ |
| $\cdot \mathbf{u}_{3}=\frac{\mathbf{u}_{3}^{\prime}}{\left\\|\mathbf{u}_{2}^{\prime}\right\\|}$ | Normalization of vector $\mathbf{u}_{3}^{\prime}$ |
| $\cdot \mathbf{u}_{m}^{\prime}=\mathbf{v}_{m}-\sum_{i=1}^{n-1} \frac{\left\langle\mathbf{v}_{m}, \mathbf{u}_{i}\right\rangle}{\left\langle\mathbf{u}_{i} \mathbf{u}_{\rangle}\right\rangle} \mathbf{u}_{i}$ | Orthogonalization of $\mathbf{v}_{\boldsymbol{m}}$ |
| - $\mathbf{u}_{m}=\frac{\mathbf{u}_{m}^{\prime}}{\left\\|\mathbf{u}_{m}^{\prime}\right\\|}$ | Normalization of vector $\mathbf{u}_{m}^{\prime}$ |

https://upload.wikimedia.org/wikipedia/commons/e/ee/Gram-Schmidt_orthonormalization_process.gif

## Gram Schmidt Orthogonalization



## Gram Schmidt Orthogonalization

Applications

Find an orthonormal basis for given vectors

How to truncate the basis?

- Engineering Knowledge: Select appropriate snapshots to calculate the basis

Used in different numerical algorithms (e.g. for the calculation of Krylov subspaces)

## How to find a good Subspace

## Proper Orthogonal Decomposition

## EuroSime

CADFEM
/nsys
CHANNEL PARTNER


## Proper Orthogonal Decomposition

## Target

Find the best linear subspace for the approximation of the data
$\mathbf{S}=\left[\mathbf{y}_{1}, \ldots \mathbf{y}_{n}\right] \in \mathbb{R}^{N \times m}$

```
Principal Component Analysis
Compute the eigenvalue decomposition of }\mathbf{Y}=\mp@subsup{\mathbf{SS}}{}{T}\quad\in\mp@subsup{\mathbb{R}}{}{N\timesN
->Sorted Eigenvalues }\boldsymbol{\lambda}={\mp@subsup{\lambda}{1}{},\ldots,\mp@subsup{\lambda}{N}{}}\mathrm{ and Eigenvectors }\boldsymbol{\Psi}=[\mp@subsup{\Psi}{1}{},\ldots,\mp@subsup{\Psi}{N}{}
Basisvectors }\mp@subsup{\boldsymbol{\Phi}}{i}{}=\mp@subsup{\boldsymbol{\Psi}}{i}{}\in\mp@subsup{\mathbb{R}}{}{N
```

```
Method of Snapshots
Compute the eigenvalue decomposition of }\quad\mathbf{Y}=\mp@subsup{\mathbf{S}}{}{T}\mathbf{S}\quad\in\mp@subsup{\mathbb{R}}{}{m\timesm
->Sorted Eigenvalues }\boldsymbol{\lambda}={\mp@subsup{\boldsymbol{\lambda}}{1}{},\ldots,\mp@subsup{\lambda}{N}{}}\mathrm{ and Eigenvectors }\boldsymbol{\Psi}=[\mp@subsup{\Psi}{1}{},\ldots,\mp@subsup{\Psi}{N}{}
Basisvectors }\mp@subsup{\boldsymbol{\Phi}}{i}{}=\mathbf{S}\mp@subsup{\Psi}{i}{}\in\mp@subsup{\mathbb{R}}{}{N
```

Best Linear Approximation
Take $n$ basisvectors corresponding to the largest eigenvalues

## Proper Orthogonal Decomposition

## Use Cases

## Principal Component Analysis

- Compute the eigenvalue decomposition of $\mathbf{Y}=\mathbf{S S}^{\mathrm{T}} \quad \in \mathbb{R}^{N \times N}$
- Efficient if length $N$ of snapshot vectors (e.g. locations) is low compared to count $m$ of snapshots (e.g. timesteps)
$\rightarrow$ Measurement data
Method of Snapshots
-Compute the eigenvalue decomposition of $\mathbf{Y}=\mathbf{S}^{\mathrm{T}} \mathbf{S} \quad \in \mathbb{R}^{m \times m}$
- Efficient if count $m$ of snapshots (e.g. timesteps) is low compared to length $N$ of snapshot vectors (e.g. locations)
$\rightarrow$ Simulation data



## Summary





