FAULT DIAGNOSIS OF THERMAL TURBOMACHINES USING SUPPORT VECTOR MACHINES (SVM)

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FAULT DIAGNOSIS OF THERMAL TURBOMACHINES USING SUPPORT VECTOR MACHINES (SVM)

- Description of the diagnostic problem

- Support Vector machines (SVM)
  - The mechanism behind
  - The general classification case

- Application on a Turbofan Engine
  - Aerothermodynamic benchmark fault cases
  - Sensor fault diagnosis

- Application on compressor faults
  - The radial compressor case
  - The axial compressor case

- Summary - Conclusions
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Description of the diagnostic problem

\[ u \text{ (operating point)} \rightarrow f \text{ (health condition)} \rightarrow Y \text{ (measurements)} \]

Engine faults (represented by a health parameters deviation), cause a corresponding measurement deviation.

Given a set of measurements the goal is to estimate the health parameters deviation due to fault.
Fault Diagnosis of Thermal Turbomachines using Support Vector Machines (SVM)

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Support Vector Machines (SVM)

SVM is a supervised learning technique used for pattern classification

\[
\text{margin} = \frac{2}{||w||}
\]

\[
\varepsilon_1 : \quad w \cdot x + b = +1 \\
\varepsilon_2 : \quad w \cdot x + b = -1 \\
\varepsilon : \quad w^* \cdot x + b^* = 0
\]

All points satisfy:

\[
\begin{align*}
\tilde{w} \cdot \tilde{x} + b & \geq +1, \quad y = +1 \\
\tilde{w} \cdot \tilde{x} + b & \leq -1, \quad y = -1 \\
y_i (\tilde{w} \cdot \tilde{x}_i + b) - 1 & \geq 0, \quad \forall i
\end{align*}
\]

Linear SVM, with fully separable classes of 2D points
Support Vector Machines (SVM)

Quadratic Programming optimization problem

Laplace transform

Karush-Kuhn-Tucker (KKT) conditions

$$\max \left( \frac{2}{\| \vec{w} \|} \right) \rightarrow \min \left( \frac{1}{2} \| \vec{w} \|^2 \right)$$

$$y_i ( \vec{w} \cdot \vec{x}_i + b ) - 1 \geq 0, \ \forall i$$

$$\max : Ld = \sum_{i=1}^{l} a_i - \frac{1}{2} \sum_{i,j=1}^{l} a_i a_j y_i y_j x_i x_j$$

$$\sum_{i=1}^{l} a_i y_i = 0$$

$$a_i \geq 0$$
Support Vector Machines (SVM)
Pattern classification

Class y=+1

\[ \mathbf{w} \cdot \mathbf{x} + b = 0 \]

Class y=-1

\[ \mathbf{w}^* \cdot \mathbf{x} + b^* = \pm 1 \rightarrow b^* \]

\[ \mathbf{w}^* = \sum_{i=1}^{l} a_i y_i \mathbf{x}_j \rightarrow \mathbf{w}^* \]

\[ \mathbf{w}^* \cdot \mathbf{x}_i + b^* > 0 \Rightarrow \mathbf{x}_i \in y = +1 \]

\[ \mathbf{w}^* \cdot \mathbf{x}_2 + b^* < 0 \Rightarrow \mathbf{x}_2 \in y = -1 \]
Support Vector Machines (SVM) – The general case

Non-linear SVM, with non-separable classes

\[
\begin{align*}
\text{max} : \quad & Ld = \sum_{i=1}^{l} a_i - \frac{1}{2} \sum_{i,j=1}^{l} a_i a_j y_i y_j \cdot K(x_i, x_j) \\
\sum_{i=1}^{l} a_i y_i &= 0 \\
0 \leq a_i &\leq C
\end{align*}
\]

Considered Kernel functions:

- **Linear kernel**
  \[ K(x, y) = x \cdot y \]

- **Polynomial kernel**
  \[ K(x, y) = (\text{gamma} \cdot (x \cdot y) + \text{coef})^{\text{degree}} \]

- **RBF kernel**
  \[ K(x, y) = e^{-\text{gamma} \|x-y\|^2} \]

- **Sigmoid kernel**
  \[ K(x, y) = \tanh(\text{gamma} \cdot (x \cdot y) - \text{coef}) \]
Support Vector Machines (SVM)
Multiclassification; the case of more classes involved

- One-against-all
- All-together
- One-against-one
- DAGSVM

Max-wins classification

<table>
<thead>
<tr>
<th></th>
<th>Class-1</th>
<th>Class-2</th>
<th>Class-3</th>
</tr>
</thead>
<tbody>
<tr>
<td>ε1-2</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>ε1-3</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>ε2-3</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>total</td>
<td>1</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>
Overall diagnostic procedure

Filtered percentage deviations of available measurements form the input patterns
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Summary - Conclusions
Application on a Turbofan engine

Twin spool, high-by-Pass ratio, turbofan engine used as a test case
### Application on a Turbofan engine

<table>
<thead>
<tr>
<th>no. of classes</th>
<th>parameter deviations</th>
<th>no. of classes</th>
<th>parameter deviations</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>$\Delta f_i = \alpha$, $\alpha \in [-2.5%, -2.0%]$, $f^i = A8IMP, SW_i, SE_i$, $i=12,2,26,41,49$</td>
<td>3</td>
<td>$(\Delta SW_i = \alpha, \Delta SE_i = -\alpha)$, $\alpha \in (1.0%, 1.5%)$, $i=26,41,49$</td>
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</tr>
<tr>
<td>11</td>
<td>$\Delta f_i = \alpha$, $\alpha \in (-1.0%, -0.5%)$, $f^i = A8IMP, SW_i, SE_i$, $i=12,2,26,41,49$</td>
<td>3</td>
<td>$(\Delta SW_i = \alpha, \Delta SE_i = -\alpha/2)$, $\alpha \in [0.5%, 1.0%]$, $i=26,41,49$</td>
</tr>
<tr>
<td>4</td>
<td>$\Delta f_i = \alpha$, $\alpha \in [0.5%, 1.0%]$, $f^i = A8IMP, SW_i$, $i=26,41,49$</td>
<td>3</td>
<td>$(\Delta SW_i = \alpha, \Delta SE_i = -\alpha/2)$, $\alpha \in (1.0%, 1.5%)$, $i=26,41,49$</td>
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</tr>
<tr>
<td>5</td>
<td>$(\Delta SW_i = \alpha, \Delta SE_i = \alpha)$, $\alpha \in [-2.5%, -2.0%]$</td>
<td>1</td>
<td>$(\Delta SW_12 = \alpha, \Delta SE_12 = \alpha, \Delta SW_2 = \alpha, \Delta SE_2 = \alpha)$, $\alpha \in [-2.5%, -2.0%]$</td>
</tr>
<tr>
<td>5</td>
<td>$(\Delta SW_i = \alpha, \Delta SE_i = \alpha)$, $\alpha \in [-2.0%, -1.5%]$</td>
<td>1</td>
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<tr>
<td>5</td>
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<td>1</td>
<td>$(\Delta SW_12 = \alpha, \Delta SE_12 = \alpha/2, \Delta SW_2 = \alpha, \Delta SE_2 = \alpha/2)$, $\alpha \in [-1.0%, -0.5%]$</td>
</tr>
<tr>
<td>3</td>
<td>$(\Delta SW_i = \alpha, \Delta SE_i = -\alpha)$, $\alpha \in [0.5%, 1.0%]$</td>
<td>133</td>
<td>total no. of classes</td>
</tr>
</tbody>
</table>

A number of classes were considered, each indicating a specific fault condition, represented by a deviation of health parameters within a range of values.
Application on a Turbofan engine

\[ \bar{n}_u + \bar{u}_{\text{actual}} \rightarrow \text{EPM} \]

\[ \bar{Y}_{\text{actual}} + \bar{n}_Y \rightarrow \text{EPM} \]

\[ \bar{f} = 0 \rightarrow \text{EPM} \]

\[ \bar{Y}' \]

\[ \Delta \bar{Y}' = \frac{\bar{Y}' - \bar{Y}'_o}{\bar{Y}'_o} \]

Classes populated with simulated patterns representing health parameters deviation within the range of ±[0.5%, 2.5%]
Application on a Turbofan engine

<table>
<thead>
<tr>
<th>fault case</th>
<th>actual parameter deviation</th>
<th>estimated parameter deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>SW2=-0.7%, SE2=-0.4% SW12=-1%, SE12=-0.5%</td>
<td>SW2=-0.7%, SE2=-0.4% SW12=-0.7%, SE12=-0.5%</td>
</tr>
<tr>
<td>b</td>
<td>SE12=-1%</td>
<td>SE12=-1.2%</td>
</tr>
<tr>
<td>c</td>
<td>SW26=-1%, SE26=-0.7%</td>
<td>SE26=-1.2%</td>
</tr>
<tr>
<td>d</td>
<td>SE26=-1%</td>
<td>SE26=-1.2%</td>
</tr>
<tr>
<td>e</td>
<td>SW26=-1%</td>
<td>SW26=-1.2%</td>
</tr>
<tr>
<td>f</td>
<td>SW41=+1%</td>
<td>SW41=+0.75%</td>
</tr>
<tr>
<td>g</td>
<td>SW41=-1%, SE41=-1%</td>
<td>SW41=-1.2%, SE41=-1.2%</td>
</tr>
<tr>
<td>h</td>
<td>SE41=-1%</td>
<td>SE41=-1.2%</td>
</tr>
<tr>
<td>i</td>
<td>SE49=-1%</td>
<td>SE49=-1.2%</td>
</tr>
<tr>
<td>j</td>
<td>SW49=-1%, SE49=-0.4%</td>
<td>SW49=-1.2%, SE49=-0.6%</td>
</tr>
<tr>
<td>k</td>
<td>SW49=-1%</td>
<td>SW49=-1.2%</td>
</tr>
<tr>
<td>l</td>
<td>SW49=+1%, SE49=-0.6%</td>
<td>SW49=+0.75%, SE49=-0.4%</td>
</tr>
<tr>
<td>m</td>
<td>A8IMP=+1%</td>
<td>A8IMP=+1.3%</td>
</tr>
<tr>
<td>n</td>
<td>A8IMP=-1%</td>
<td>A8IMP=-1.2%</td>
</tr>
<tr>
<td>o</td>
<td>A8IMP=+2%</td>
<td>A8IMP=+1.8%</td>
</tr>
</tbody>
</table>

Results based on benchmark fault cases delivered by engine manufacturer
### Application on a Turbofan engine

SVM applied for sensor fault diagnosis

#### Classes Definition

- **Sensors deviation**: ±(1.0, 2.0)%
- **Health parameters deviation**: (-2.5%, -1.5%, 0%, +1.5%, +2.5%)

#### Examined Patterns

- **Sensors deviation**: ±1.5%
- **Health parameters deviation**: (-2.5%, -1.5%, 0%, +1.5%, +2.5%)

#### Simulated sensor biases for all available sensors, at the simultaneous presence of component faults, where examined

<table>
<thead>
<tr>
<th>SVM</th>
<th>wrong estimations</th>
<th>score</th>
</tr>
</thead>
<tbody>
<tr>
<td>LINEAR</td>
<td>640</td>
<td>0.0%</td>
</tr>
<tr>
<td>POLYNOMIAL</td>
<td>43</td>
<td>93.3%</td>
</tr>
<tr>
<td>SIGMOID</td>
<td>450</td>
<td>1.6%</td>
</tr>
<tr>
<td>RBF</td>
<td>1</td>
<td>99.8%</td>
</tr>
</tbody>
</table>
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Application on compressor faults
actual implemented mechanical faults on two compressors

Radial Compressor

Axial Compressor
Application on compressor faults
Faults Examined: Radial Compressor

Available data consist of:
- 4 sets of 7 thermodynamic data
- 4 sets of 1 fast response measurement

Inlet Distortion  Diffuser Fault  Impeller Fouling
Application on compressor faults
Faults Examined: Axial Compressor

Implemented faults:
- Fouled Rotor of Stage 2
- Two blades of Rotor 1 fouled
- Twisted blade of Rotor 1
- Three mistuned stator vanes

Available data consist of:
- 4 sets of 7 thermodynamic data
- 4 sets of 4 fast response measurements
Application on compressor faults
results on original and additional data

- Linear
- Polynomial
- RBF
- Sigmoid

original data
additional data
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Summary - Conclusions

• A Support Vector Machine (SVM) method, for gas turbine faults classification and diagnosis, has been presented.

• SVM is a well-known and efficient classification technique that in this work has been used as a stand-alone diagnostic method, supported by an Engine Performance Model.

• SVM efficiency has been examined through application on a number of realistic fault conditions that may encounter in practice on a gas turbine, including aerothemrodynamic faults, sensor faults and mechanical faults.

• The performance of SVM under all examined fault condition indicate that SVM is a powerful technique for Gas Turbine diagnosis.