Eigenmode Identification in Campbell Diagrams

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Abstract

Jet engines need to be certified before going into service, i. e., any dangerous vibration has to be detected. Therefore the eigenmodes, displayed as curves in Campbell diagrams, need to be identified first. At the moment this is done manually by engineers. In this paper we introduce a way of automatically detecting eigenmodes in Campbell diagrams by introducing an extension of Hough transform.

1 Introduction

Jet engines need to be certified before going into service: dangerous vibrations have to be detected and resolved by redesign. The vibration data is usually visualized as image, called Campbell diagram, having speed on the x-axis and frequency on the y-axis. The stress (or intensity of vibration) is usually encoded in the color value of the pixel at any given speed and frequency coordinate. In this diagram, characteristic patterns can be observed: for example the so called Eigenmodes are quadratic curves that can be approximated by lines (as linear terms usually dominate). Analysis of Campbell diagrams is usually performed manually by the engineers. They use two sources of background information: predictions from the Finite Element Model (FEM) of the engine components and results of sensor (strain gauge) calibration experiments from the laboratory. Our approach aims at supporting this analysis with machine learning techniques.

Components in jet engines are exposed to vibrations caused by unsteady forces, i. e., relative motions of rotating and non-rotating parts. Vibration in general can be described by the equation of motion,

$$kx + c\dot{x} + m\ddot{x} = f,$$

a differential equation which describes a system consisting of a spring k, a damper c and a mass m. Furthermore, x describes the displacement of the system. These components determine the force f.

There are two different kinds of vibrations:

1. Every component has a series of natural frequencies, also called eigenmodes or eigenfrequencies, which are the frequencies where the component vibrates freely.
2. A system has a series of excitation frequencies (also called excitation orders), which are time-dependant due to rotational motion.

In Campbell diagrams, eigenmodes are represented as nearly horizontal lines. Excitation orders can be seen as linear functions having zero offset. Their slope can be calculated for a given engine, while their intensity is variant and needs to be measured during tests. Resonance, i. e., oscillation at the system's maximum amplitude, occurs at the intersection points of eigenmodes and excitation frequencies in Campbell diagrams. Intersection points (high stresses) lead to high cycle fatigue, i. e., the component brakes after a number of cycles [1]. Campbell diagrams are usually recorded during engine tests. The aim of the engineers is to detect those resonance points. Currently they are doing this by manually analyzing the eigenmodes in Campbell diagrams and using additional information from measurements taken beforehand. In this paper we concentrate on automating the eigenmode identification.

The problem can be described as follows: Given an image i containing both eigenmodes and excitation orders, find all visible lines and dissect eigenmode lines (L_e^i) from excitation order lines. An eigenmode $l \in L_e^i$ can be described using the slope-intercept form, i.e., having frequency $f(t) = \tan^{-1}(\beta)t + \mathrm{y}_0$. For the slope we are using the angle representation denoted by β. Furthermore, two sets of eigenmodes are given: L_{lab}^i denotes the set of eigenmodes from sensor calibration experiments; L_{FEM}^i contains predictions for eigenmodes from the FEM.

In the eigenmode identification problem, it is also important to assign the unique so called eigenmode number to the lines. However, not all possible eigenmodes are always present in a Campbell diagram, thus some of the eigenmode numbers will not be assigned. This makes the assignment of eigenmode numbers a difficult problem.

2 Method Description

The objective of our method is to detect eigenmodes in a Campbell diagram. Eigenmodes are usually blurred and lie close to each other. Our approach is based on Hough Transform [2,3] and uses background knowledge (L_{lab}^i, L_{FEM}^i). Hough Transform is used in image analysis for recognition of lines or other parameterizable shapes. The algorithm is given in figure 1:

HoughTransform$(i, \beta_{min}, \beta_{max})$:
$\forall\, (x, y) \in i$:
for $\beta \in [\beta_{min}, \beta_{max}]$ **do**
    $y_0 := y - x \cdot \tan(\beta)$
    $H[\beta][y_0] = H[\beta][y_0] + (x, y)$
    $H[\beta][y_0 - 1] = H[\beta][y_0 - 1] + \lambda \cdot (x, y)$
    $H[\beta][y_0 + 1] = H[\beta][y_0 + 1] + \lambda \cdot (x, y)$
od
return H

Figure 1: Simple Hough Transform

Hough Transform takes an image i and an interval of slopes (angles from β_{min} to β_{max}) as input. For each pixel $(x, y) \in i$ it calculates which lines this pixel may belong to. These lines are characterized by their offset y_0 and slope β. The stress (color value) at $(x, y) \in i$ votes for all possible lines to which that pixel may belong. These votes are stored in the accumulator array H. To reduce the effect of blurring, we transfer the intensity at pixel (x, y) not only for position (β, y_0) (to which it actually belongs), but also to two of its neighbors, $(\beta, y_0 - 1)$ and $(\beta, y_0 + 1)$. We empirically set λ to 0.8. Obviously, $\arg\max_{(\beta, y_0)} H$ denotes the most significant line in image i.

For the eigenmode lines being blurred in the campbell diagrams, several (local) maxima in H may correspond to the same line (since they only differ slightly in either β, or y_0). Thus, traditional hough transform needs to be extended, as shown in figure 2. Here Hough Transform is performed several times. After each iteration, the most significant line in the accumulator array H is deleted with a width of w from the original image. The line is only added to $\hat{L}$ if it is not an excitation order. Excitation orders cross the origin, mode line do not. However, as the lines are blurred, we can not expect that excitation orders have exactly zero offset. Thus the currently found line is considered as eigenmode if the offset of a line is greater than *offset threshold* θ. To calculate θ, we average the minimal offset in L_{lab}^i and the minimal offset in L_{FEM}^i and take the half of it. Estimations of w: to be noise-robust the deletion width w should be as large as possible under the condition that no other line will be deleted, only the currently found one. We average the minimum distance of lines in L^i_{lab} and the minimal distance of lines in L^i_{FEM}. As deleting in both directions (upper and lower from the current line) with this average distance might cause the elimination of an other mode line having the minimal distance to the currently detected one, this average has to be reduced. Currently, we simply multiplied it by 0.75. If very few lines are contained in L^i_{lab} or L^i_{FEM}, the average might be too high, thus we restrict w not to exceed a user-defined maximum (w_{max}).

```
iterativeHT(i, K, w, θ, β_min, β_max)
L_e^i := ∅,   k = 0
while k < K do
        H = HoughTransform(i, β_min, β_max)
        (β, y_0) = arg max_{(β,y_0)∈H} H
        if y_0 > θ
           L_e^i = L_e^i ∪ {(β, y_0)},   k = k + 1
        fi
        delete line (β, y_0) from image i with width w
od
return L_e^i
```

Figure 2: Iterative Hough Transform

The algorithm presented so far recognizes lines in terms of their offsets and slopes. To assign eigenmode numbers we match the lines recognized by Hough Transform either *i)* to the eigenmode lines in the Finite Element Model L^i_{FEM}, or *ii)* to the eigenmodes in L^i_{lab} and use that eigenmode numbers as predictions for the detected lines.

To quantify the differences between lines we use the integral between them. There are different possibilities to match the recognized lines to the lines in the background model. We implemented:

1. *GreedyBestFitMatch:* For each detected line $l_e \in L^i_e$ we determine its pair $p(l_e) \in L^i_{lab}$ or L^i_{FEM}. (p is not necessary bijective.) Let l'_e =argmin$_{l_e \in L^i_e}$\{difference$(l_e, p(l_e))$\}. We assign the mode number of $p(l'_e)$ to l'_e. We remove l'_e from L_e, and $p(l'_e)$ from L^i_{lab} or L^i_{FEM}. We repeat it until no eigenmodes are left in L^i_{lab} or L^i_{FEM}.
2. *PriorityMatch:* We take into account the detection order of lines in an image and first match those lines to eigenmodes in L^i_{lab} or L^i_{FEM} which have been found first.

As both matching techniques are greedy, we perform local search to optimize the difference between the recognized lines and the lines in the background model.

3 Preliminary Evaluation

As our work is still on-going, we only present preliminary results of our evaluation. For evaluating our approach we used a real-life data set from a major jet engine manufacturer consisting in total of 201 Campbell diagrams from 14 engine tests performed on one engine. Tests performed several times using the same settings resulted in equivalent Campbell diagrams. To reduce noise and make eigenmode lines clearer, as a preprocessing step we aggregated the equivalent Campbell diagrams pixelwise. This led to 42 non-equivalent Campbell diagrams. Furthermore the data set contained in total 571 FEM eigenmode predictions and 271 eigenmodes detected in the laboratory in total (i.e. on average 14 FEM predictions and 6-7 lab-detected eigenmodes per diagram). We measured the quality of our new approach by Root Mean Squared Error (RMSE) regarding the area (integral) between the detected line l_j and the true (annotated) line l^a_j. We performed mode line recognition and calculated RMSE for each Campbell diagram individually, we report the avergage of them.

$$RMSE = \sqrt{\frac{\sum_{j=1}^{|L^i_e|} (\int |l_j - l^a_j|)^2}{|L^i_e|}}$$

We performed three experiments. According to domain experts' advise we set the hyperparameter K to 30 in both experiments. The first experiment aims at evaluating the accuracy of our line recognition algorithm (i.e., without evaluating the assignment of eigenmode numbers), the 2nd and 3rd experiment assesses the overall quality of our approach including the assignment of eigenmode numbers. In the first experiment setting we matched the detected lines to the eigenmodes annotated by experts (GreedyBestFitMatch with local search). Figure 3 shows the results of this experiment. Here, HTBK_x denotes our approach, Lab and FEM are the baselines: RMSE for lines in L^i_{lab} and L^i_{FEM}. To ensure fair comparision, in HTBK_Lab and HTBK_FEM for each Campbell diagram i the count of matched and evaluated lines correpsond to the count of lines in L^i_{lab} and L^i_{FEM} respectively. Our algorithm clearly outperforms the baselines, i.e. L^i_{lab} and L^i_{FEM}.

In the 2nd experiment we first matched the detected lines against L^i_{FEM} and measured the RMSE regarding the area between detected lines (assigned with the eigenmode numbers in matching step) and annotated lines. The results are shown in figure 4. We see that our approach performs better than the FEM model, the best results were achieved with Priority Matching with local search. The 3rd experiment is similar to the 2nd one, but we matched the detected lines against L^i_{lab}. Results are depicted in figure 5. We see that our algorithm has nearly the same performance as the lab model, which it is already very accurate. It must be noted that lab measurements are taken on only a few components, s. t. only a few lines are available at all. Here the best results have been achieved with Greedy Best Fit without local search.

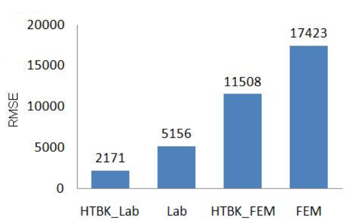

Figure 3: Mode line detection without mode number assignment

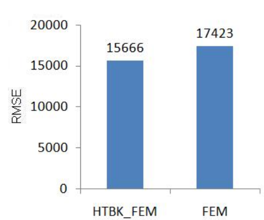

Figure 4: Mode line detection and mode number assignment with L^i_{FEM}

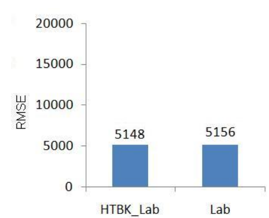

Figure 5: Mode line detection and mode number assignment with L^i_{lab}

4 Conclusion

We presented an extension to Hough Transform which has been shown to have high line recognition accuracy of eigenmodes. Furthermore, HTBK is able to improve the accuracy of the both background models, i.e. L^i_{lab} and L^i_{FEM} in terms of RMSE. Future work will extend our work in several directions. Additional background knowledge will be used to further improve both line detection and mode number assignment. For the latter one, we will also use supervised machine learning methods.

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5 References

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