Anomaly Detection in Aircraft Engine Vibration Using Deep Convolutional Autoencoder

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Abstract

The useful life of aircraft engines depends on their operating environment (polluted areas, harsh climate, etc.). Detecting signs of degradation and aging can be difficult due to background noise measured on vibrational signals. Statistical methods such as threshold-based monitoring may not be reliable enough. This paper presents a promising method based on learning normal behavior on a population of engines considered to be healthy, such as newly produced engines. The learning is done by calculating spectrograms of the vibrational signals, normalizing them and treating them as images, then using a convolutional autoencoder to learn normal behavior. This model can be used during shop visits to detect early degradation by comparing vibrational signals of in-use engines to the learned standard.

Keywords: vibrational signals, background noise, normal behavior, convolutional autoencoder.

1 Introduction

The legacy engines, which were produced in the 2000s, have seen a growing number of instances where they are being sent back to repair shops in recent years. Safran Aircraft Engine's Vibratory Health Monitoring team plays an important role in monitoring the vibratory health of the bearings in these engines. Currently, algorithms based on indicators and Fourier transforms are used to assist experts in analyzing the vibration health of the bearings. However, these algorithms generate false alarms due to changes in the vibration signature resulting from the aging of the legacy engines.

In this paper, we introduce an approach utilizing convolutional autoencoders to effectively learn and understand the dynamic behavior of newly produced engines. Our primary objective is to assist health vibration monitoring experts in monitoring the health status of legacy engine bearings. The proposed approach leverages the spectrograms of vibration signals, treating them as images, to train convolutional autoencoders. By doing so, our model aims to acquire a deep understanding of the normal behavior exhibited by new engines manufactured in the 2000s. Once the model is trained, we will then be able to “denoise” the spectrograms of the engines that enter the maintenance workshops by eliminating the signatures found in the spectrograms of new engines. Therefore, we simplify the analysis to the health monitoring experts at Safran Aircraft Engines.

2 The Data

To guarantee optimal performance and reliability to its customers, Safran Aircraft Engines carries out acceptance tests on the engines before their delivery. These tests include a specific maneuver called vibration survey which aims to perform a slow acceleration and deceleration. This transient maneuver aims to cover several operating modes. By performing the vibration survey maneuver, the health monitoring experts at Safran Aircraft Engines can give a status on the vibratory health of the bearings for new engines leaving the production line.

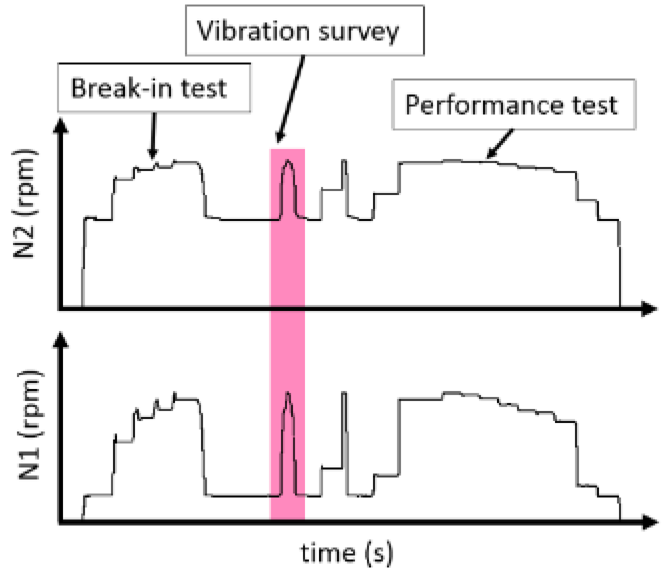

Figure 1: Examples of acceptance tests

Health monitoring experts analyse the health status of bearings, which is important for overall engine performance. To conduct this diagnosis, experts utilize the vibration survey maneuver and specifically focus on the analysis of spectrograms derived from two accelerometers attached to the engine. These spectrograms provide valuable insights into the condition of the bearings. By carefully examining the spectrograms obtained from both accelerometers, experts can provide an accurate assessment of the bearing health prior to engine delivery. The spectrograms are calculated by computing the spectrums at regular intervals (10 rpm) of the high-pressure shaft's rotating speed (N2). This process forms the spectrogram, offering a visual representation of the frequency content and changes in vibrations over time. The diagram below illustrates the process of calculating the spectrograms, aiding experts in their analysis and enabling them to make informed decisions regarding the health status of the bearings.

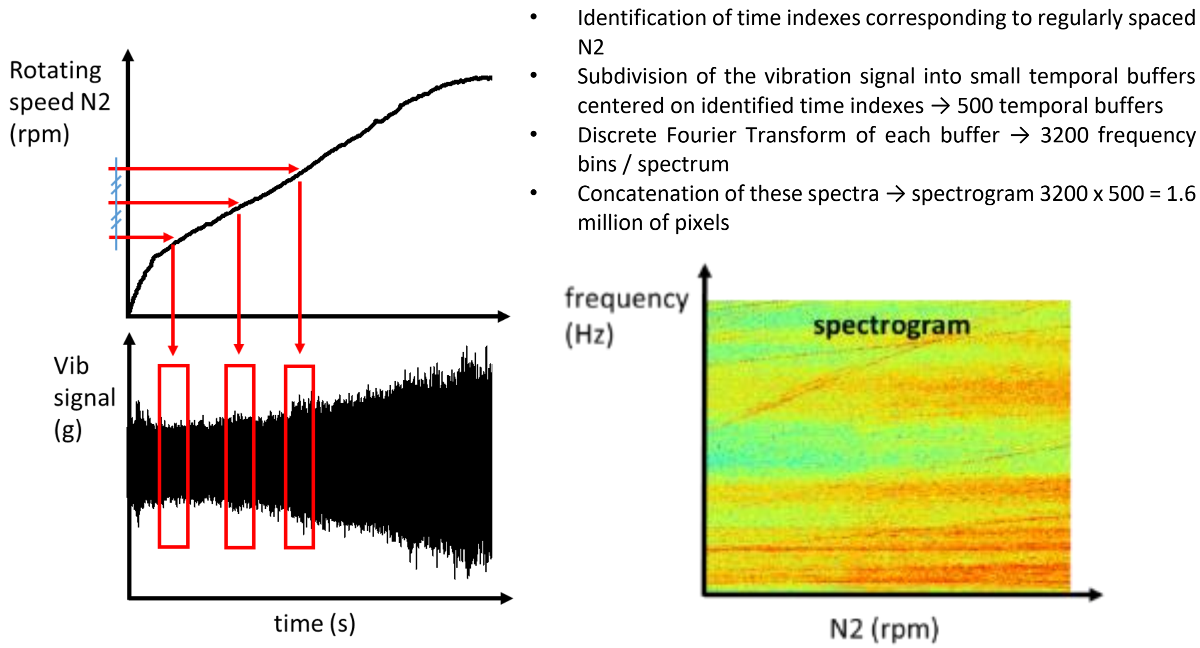

Figure 2: Diagram explaining how spectrograms are calculated and plotted based on the engine speed (N2)

3 The approach used to train the model

The main focus of this paper revolves around the training of a convolutional autoencoder to learn valuable insights into the behavior of a newly developed engine. During the transition of an aged engine to the repair shop, the expert's analysis is specifically targeted towards the residual spectrogram. This residual spectrogram is obtained by taking the difference between the spectrogram of the aged engine and the spectrogram generated by the autoencoder. By isolating this residual spectrogram, the expert can exclusively examine patterns that deviate from the vibratory signature of a new engine, allowing for the detection of potential anomalies.

To train the convolutional autoencoder, a comprehensive database comprising 3400 spectrograms was utilized, considering them as images. To stay aligned with the practices of health monitoring experts and provide more dynamic range to the amplitudes, a logarithmic scale was applied to the calculated spectrograms. The dataset was divided into a trainset consisting of 3200 engines and a validation set containing 200 spectrograms. For the test set, a separate database consisting of 140 spectrograms from aged engines was used. It is important to note that all spectrograms were standardized to the same N2 speed range and frequency zone between 0-8kHz, aligning with the zone analyzed by health monitoring experts. Following normalization, the spectrograms were resized to dimensions of 2560 x 240 pixels, resulting in a total of 614,400 pixels.

4 The AutoEncoder Model

In this study, a convolutional autoencoder model was implemented to learn the normality patterns of new engine models. The architecture of the model comprised three convolution layers and two dense layers in the encoding part, followed by a dense layer and three deconvolution layers in the decoding part. To overcome hardware limitations, maxpooling was applied to divide the frequency axis by two, reducing the number of pixels in the spectrogram images used as inputs for the autoencoder model. The diagram below depicts the architecture of the model:

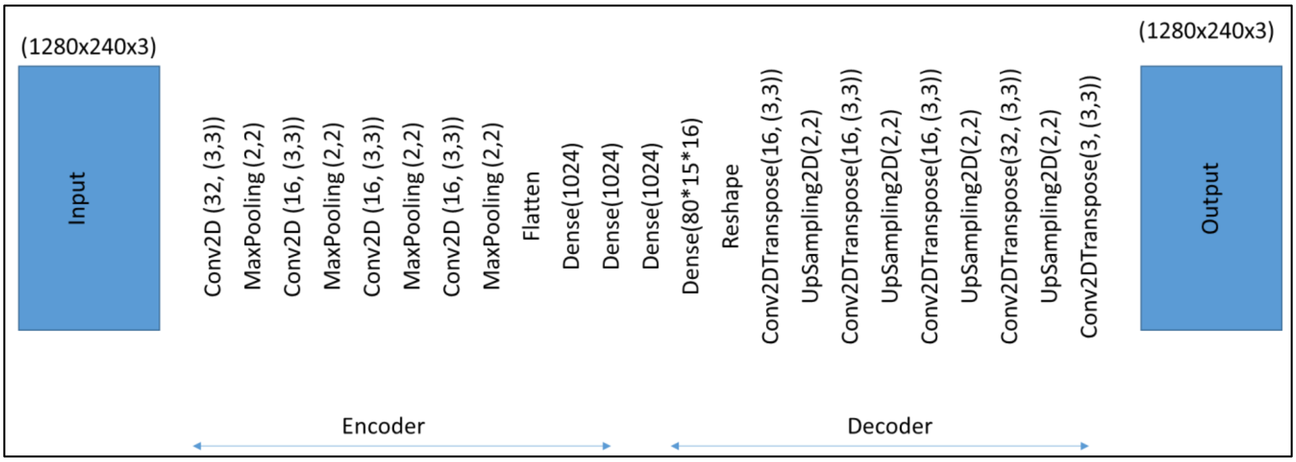

Figure 3: Diagram of the architecture of the used autoencoder.

Training the model was carried out on an Nvidia V100 GPU with 48GB of VRAM memory. The training process extended over 17 hours (680 epochs), employing a batch size of 32 images, with each epoch lasting approximately 90 seconds. The Adam solver was used for the learning process, and the mean square error was chosen as the cost function to be minimized. The learning curve of the model, displayed below, demonstrates a gradual decrease in error with each subsequent epoch, indicating the model's progressive improvement and capacity to capture relevant features.

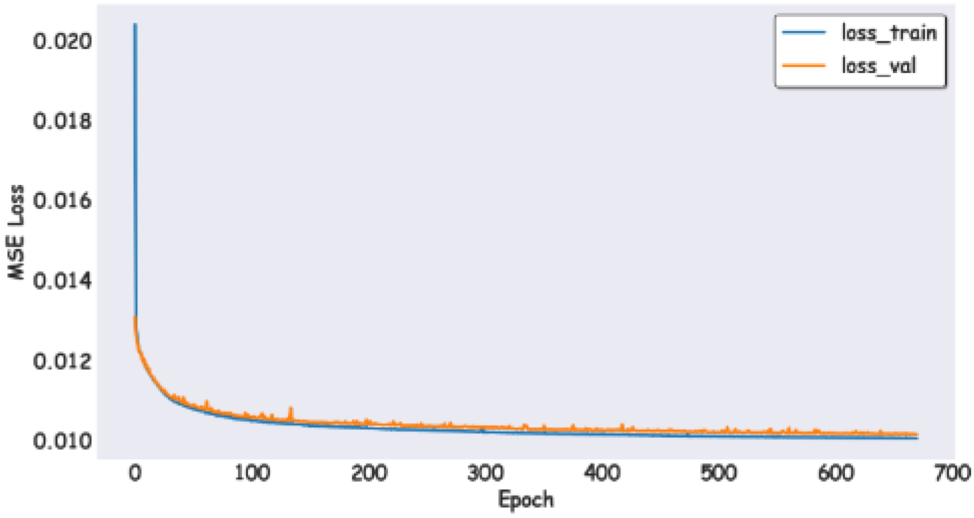

Figure 4: Error decrease during the training of the autoencoder model on both the train set and the validation set.

5 Results of the trained model

To assess the practical applicability of our approach, we carried out evaluations using the trained model on spectrograms obtained from engines subjected to workshop visits, which served as a test set. In this way, we simulated real-life conditions, enabling us to assess the performance of our model in a scenario very close to its intended use. By applying the trained model to these spectrograms, we were able to assess its ability to identify normal behavior and then focus solely on analyzing the residual spectrogram for any potential anomalies. This evaluation provided interesting insights into the effectiveness of our approach in real-life applications.

Below are some examples of results obtained with the approach proposed in this paper.

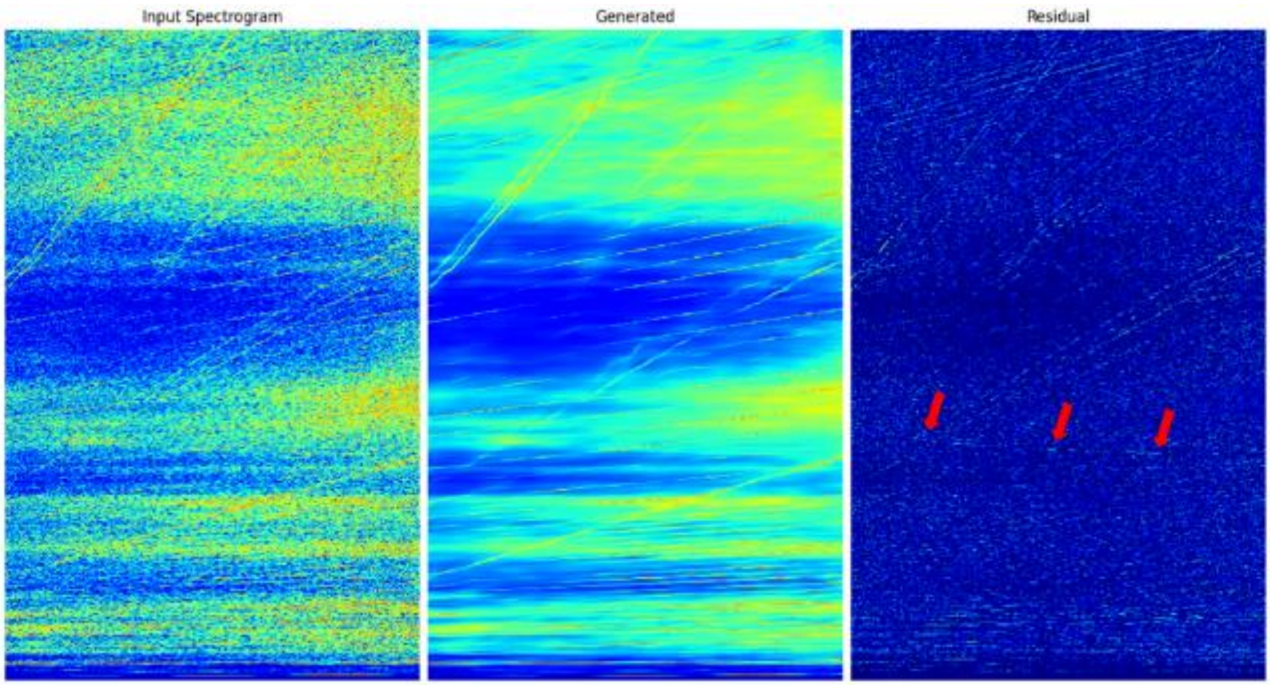

Figure 5: Spectrogram1- Analysis of the residual spectrogram obtained by the autoencoder model driven on a shop visit aged engine

The residual spectrogram revealed a bearing signature. Initially, this signature is not normal, as it is present in the residual spectrogram. This signature could indicate bearing damage or the onset of bearing deterioration.

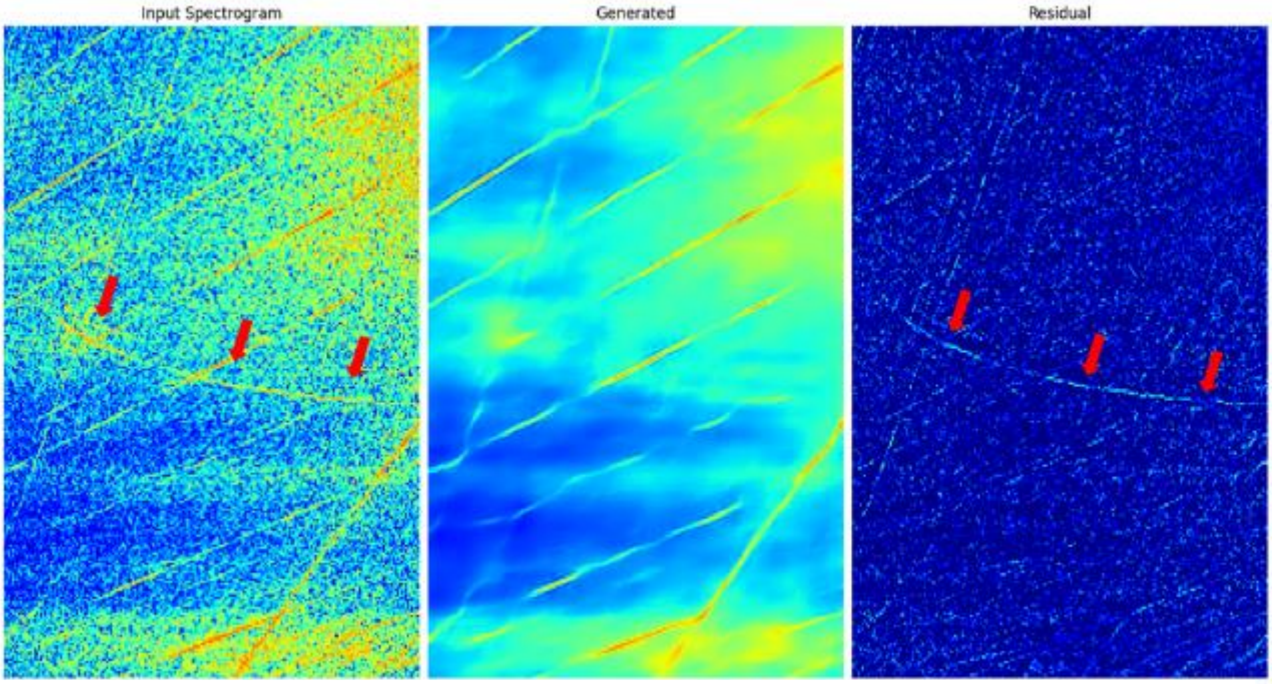

Figure 6: Zoom on spectrogram1 around the red arrows.

It can also be said that detecting this signature using indicator-based approaches is challenging because the energy of this signature is low compared to the energies of other normal engine signatures.

We will visualize below another example of a residual spectrogram with a weak damage signature.

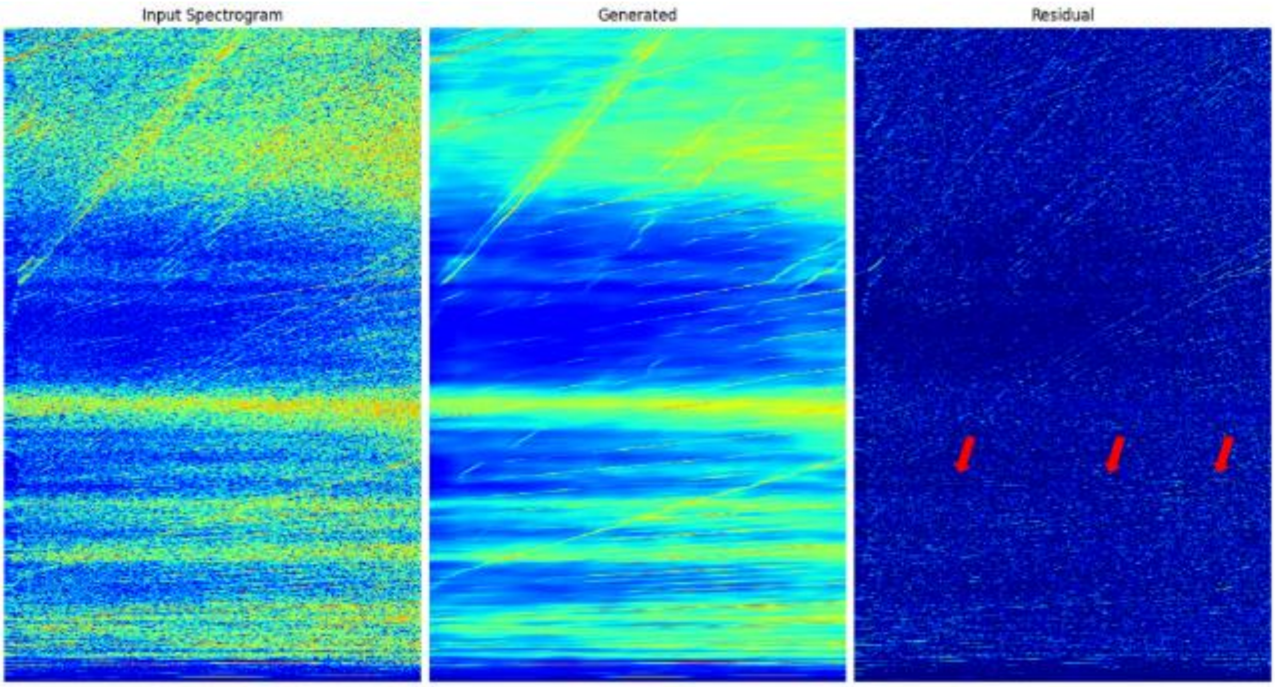

Figure 7: Spectrogram2- Analysis of the residual spectrogram obtained by the autoencoder model driven on a shop visit aged engine

The above residual displays a weak abnormal signature. Below is a zoomed-in view of this signature.

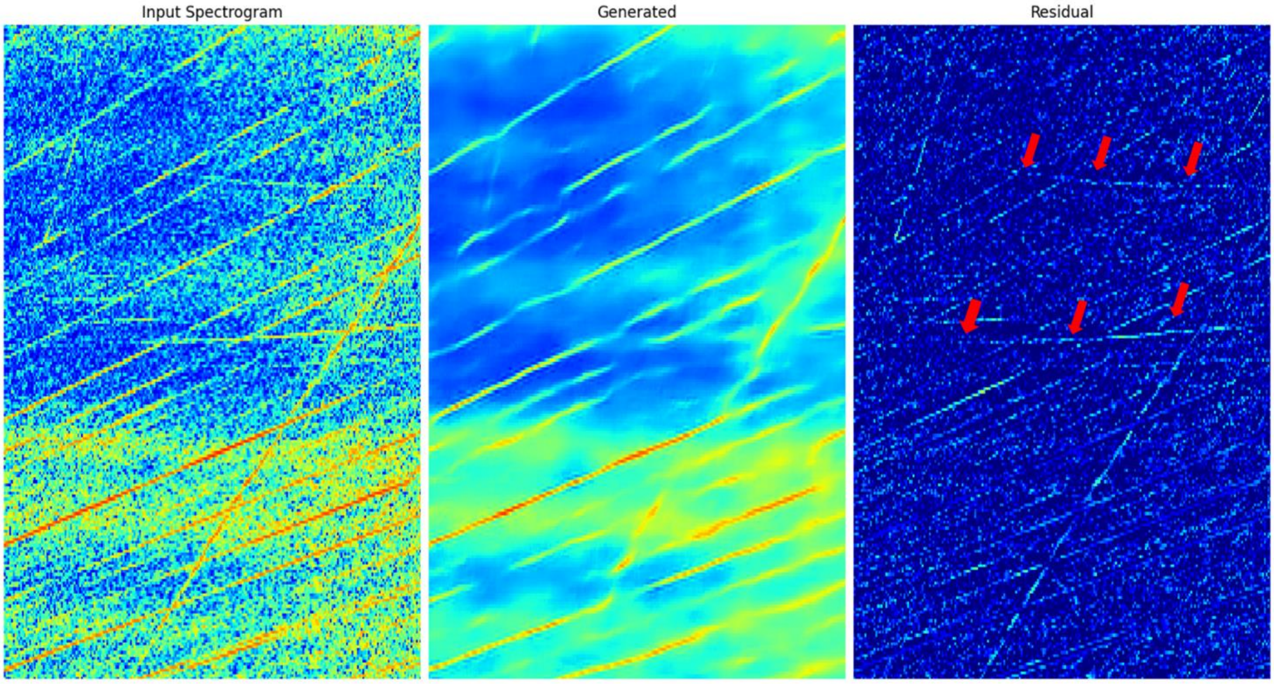

Figure 8: Zoom on spectrogram2 around the red arrows.

The zoom in the residual spectrogram reveals a weak signature of damage that remains challenging to detect on the original spectrogram. Below is a final example of an engine spectrogram obtained during a shop visit, where an abnormal symmetric signature originating from a bearing can be observed.

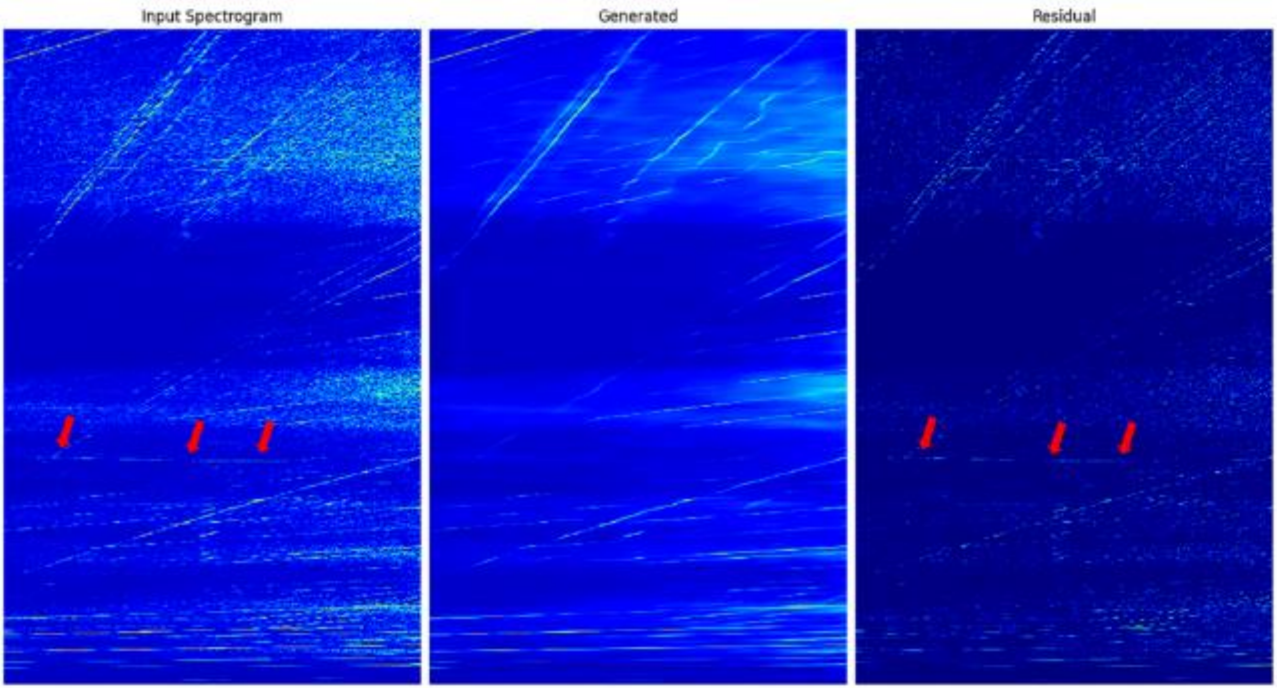

Figure 9: Spectrogram3- Analysis of the residual spectrogram obtained by the autoencoder model driven on a shop visit aged engine

The zoom around the red arrows shows a visible symmetric signature in both the original spectrogram and the residual spectrogram. This symmetric signature indicates a probable beginning of bearing damage since this signature is not typically seen in new engines.

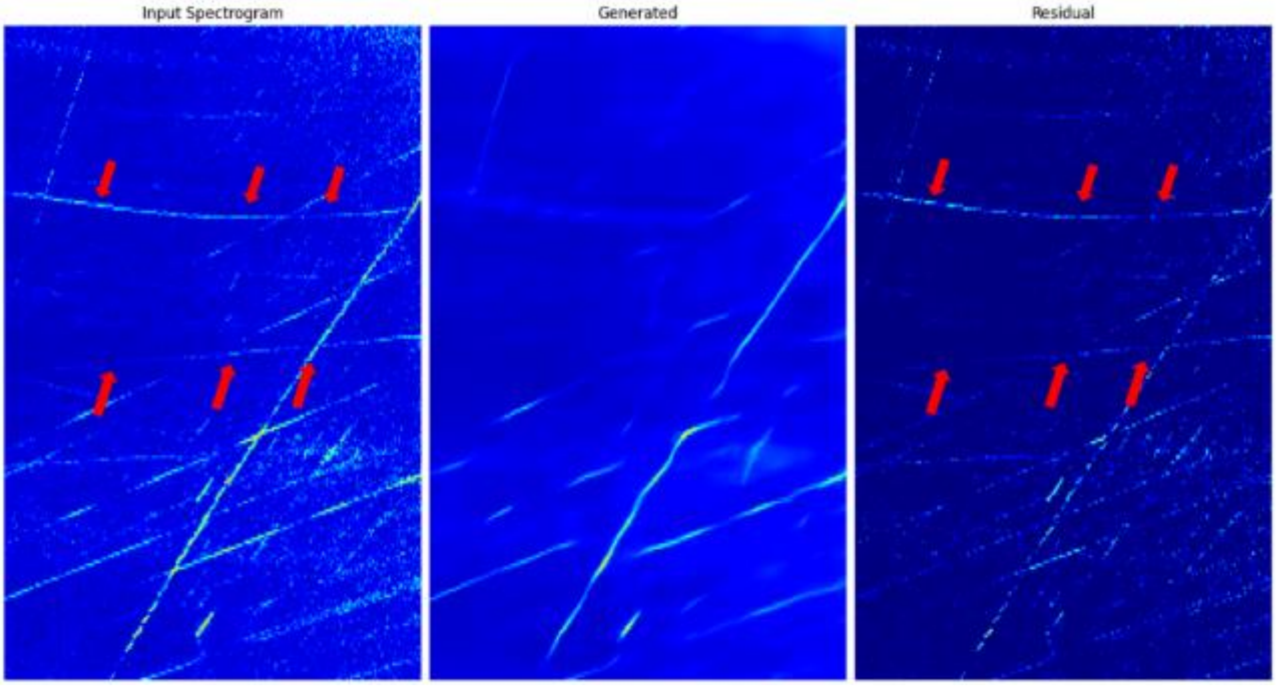

Figure 10: Zoom on spectrogram3 around the red arrows.

The examples discussed above demonstrate that the approach proposed in this paper is promising and could greatly simplify the analysis of vibrational health in bearing systems of engines during shop visits for experts in Health Monitoring at Safran Aircraft Engines. The next steps of this research will focus on developing indicators based on the residual spectrogram to automate the detection of bearing damage signatures in aged engines. This study also needs to be expanded to other applications such as the LEAP engines.

6 Conclusion

In this article, we have presented a promising approach to monitoring the vibratory health of bearings in legacy aircraft engines undergoing shop visit using convolutional autoencoders. By training our model on spectrograms of vibration signals and processing them as images, we were able to learn the normal behavior of new engines. Our approach removed much of the normal behavior from the spectrogram, providing Health Monitoring experts with a residual spectrogram that includes the differences in vibration behavior between new and aged engines. The implementation of our approach has simplified diagnosis for Health Monitoring experts, compared with approaches based on indicators and Fourier transforms. Evaluation of our model on a representative test set of aged engines undergoing shop visit validated the practical utility of our approach, demonstrating its ability to detect anomalies and facilitate diagnosis for experts. All in all, our approach is an analytical complement that helps experts make decisions on the vibration health status of aircraft engine bearings. Future work will involve further validation of our approach on larger datasets, extending the application of this method to other engine applications (such as LEAP), and exploring techniques to automate the decision-making process by setting criteria on model reconstruction error or other criteria yet to be found.

References

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