Temporal companding for the evaluation of a rotor rotation speed during strong transients

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Abstract

This paper presents a new autonomous vibration monitoring system for monitoring the mechanical health of aircraft engines.

The first section of the paper describes the new monitoring system. The constraints of the embedded part of the system are detailed. One of the most important constraints is the need to estimate the rotation speed of a rotor, from a vibratory signal, even when the rotation speed varies strongly.

The second section of the paper presents a solution to facilitate the estimation of the rotation speed when the speed varies strongly. The solution is based on a temporal companding (compressing and expanding) algorithm, which is described in detail.

In the last section, the performances and limitations of the algorithm are evaluated on some data acquired on an aircraft engine in flight.

1 Introduction

In most aircraft engine applications, one or two accelerometers are permanently fixed on the engine for the monitoring of shaft unbalances. It is yet well known that the monitoring of bearings and gears can advantageously be done with vibrations. This is why, over the past several decades, Safran Aircraft Engines has developed Health Monitoring systems based on the frequency content analysis of those existing accelerometers. Moreover, for latest applications, location and bandwidth of those accelerometers are taken into account not only for the monitoring of shaft unbalances, but also for the monitoring of bearings and gears. However, it is impossible to monitor all bearings and gears of an engine and its equipments with only two acceleremeters. The monitoring of components such as bearings and gears requires that the location of the accelerometer shall not be too far away from those components. For instance, a damaged bearing in the accessory gearbox of the engine is not detected by an accelerometer fixed on the case of the engine, because the signal of the shocks from the damaged bearing are too much attenuated between the bearing and the accelerometer. On the other hand, it is so far not realistic to multiply the number of accelerometers permanently fixed on an engine and its equipments because the weight of a sensor and its shielded cable are not negligible in the operation cost of the engine. This is why Safran Aircraft Engines proposed an alternative to the Health Monitoring traditionally done with permanently fixed accelerometers.

In a first section, we describe the new monitoring system and its constraints. More specifically, we highlight the problem of estimating a rotation speed with vibrations during strong transients.

In a second section, we describe a solution to solve this problem.

In a third section, we share the performances and limitations of this solution.

1.1 Overview of the new monitoring system with a mobile accelerometer

The main purpose of the new system is to monitor an engine and its equipments with the single measure of an accelerometer that is not permanently fixed on the engine. Since it is not possible to monitor simultaneously all components with a single accelerometer, the accelerometer of the new monitoring system shall have the capability to be easily located at several different locations.

The proposed new monitoring system has an embedded part, composed of an accelerometer connected to a storage unit, and a ground part, composed of a database with an environment for deeper postprocessing of vibrations and damage detection.

Damages detection capability and operational constraints lead to the following main characteristics:

- The embedded part shall be installed and removed under the wing in less than 15 minutes in order to be compliant with regular intervention for an airline. A consequence is that the mobile storage unit can't interface with the regulation of the engine and doesn't have access to the rotation speed of the engine shafts.
- The system must be able to monitor an engine and its equipments with the latest 50 consecutive flights, to be compliant with the delay of detection of a damaged bearing or a damaged gear.
- The maximum acquisition duration of raw data for each flight shall not exceed several minutes, for a flight average duration of several hours, due to storage capacity limitation. Consequently, the embedded part must be able to detect the appropriate operating conditions and to trigger the acquisition of vibration for several short periods of time.

In most cases, the diagnostic of damaged bearings and gears for an aircraft engine doesn't require the acquisition of vibrations throughout the duration of a flight. Appropriate operating conditions include, for instance, periods of time when the damaged surfaces of bearings and gears are loaded and generate shocks. Such conditions include periods of time with a variation of the rotation speed. For instance, at the beginning of an engine start, the rotation speed increases while the starter generates a torque that loads many bearings and gears in amplitude and direction that are not seen during any other phase of the flight. It is also impossible to define precisely for which rotation speed the signal to noise ratio of the shocks is high enough for damage detection, because the highest loads may be in a wide range of speed. Another advantage of analysing vibrations during transient conditions: it can be easier to separate excitations from sources that are not synchronous with each other, for instance excitation from static and rotating parts, or excitations from different shafts if those shafts are not synchronous with each other. Anyway, the rotation speed of at least one shaft of the engine seems to be a good candidate for the detection of appropriate operating conditions.

As a result, we propose that the embedded system should be able to perform tacholess speed estimation with vibrations.

1.2 Tacholess instantaneous speed estimation

A review of tacholess speed estimation techniques can be found in [1]. Those techniques, based on demodulation or time-frequency representation of the vibration signal, have been pooled in seven different methods. For each method, ease of implementation, computation time, number of input parameters and sensitivity to those parameters were considered. However, the main goal in the development of those techniques was the accuracy of the speed estimation.

For the embedded part of the new monitoring system, the main objective is the detection of operating conditions in real time, and therefore the constraints slightly differ from constraints considered in the development of the techniques reviewed in [1]. The new constraints can be described as follows:

- Accuracy can be rough, an error of several percent of the maximum speed is acceptable for the detection of operating conditions.
- The speed estimation must be performed for almost all operating conditions, including very low speeds and strong transients.
- Storage capacity is limited, speed estimation must be done with a short duration of time of few seconds.
- Processing capacity is limited, speed estimation must be performed with few and efficient operations.
- During the development phase of the system, the database is composed of a set of vibration raw data associated to actual measure of the speed with a tachometer. It is therefore possible to train the tacholess speed estimation, for instance with machine learning techniques.

Techniques based on time-frequency representation of the signal seem to be more compliant with those new constraints because techniques based on demodulation generally require a first estimate of the speed, which seems impossible with an embedded system processing in real time.

A preliminary analysis was done on a new dataset composed of vibrations acquired with an accelerometer fixed on the accessory gearbox of an aircraft engine. It is composed of several flights, from engine start to engine shut down. The gear mesh frequencies can be easily identified as peaks in the spectrum of the signal, at least during low speed variation.

This preliminary analysis brings to light two difficulties:

- At very low speed, the signal to noise ratio is low and the vibration signal tends to fade.
- During strong transients, the energy in the signal is smeared in several frequency bins and the gear mesh frequencies can't be easily identified in the spectrum of the signal.

The first difficulty can be easily overcome: speed below a predefined threshold can be identifed without identifying precisely the speed. Below this predefined threshold, the speed estimation shall not be required. RMS of the signal is low when the speed is low, it can be used to identify that speed shall not be estimated.

The second difficulty is described in more detail in the following chapter.

1.3 The issue of strong transients

Figure 1 shows the rotation speed of an aircraft engine shaft for 3 flights and a corresponding transient characteristic. The profile of the speed is not constant and it is not exactly repetitive from flight to flight because the speed depends on the flight plans and many parameters. It can also be seen that the ratio of the speed at two moments separated by one second can be in the order of several % and up to 60%.

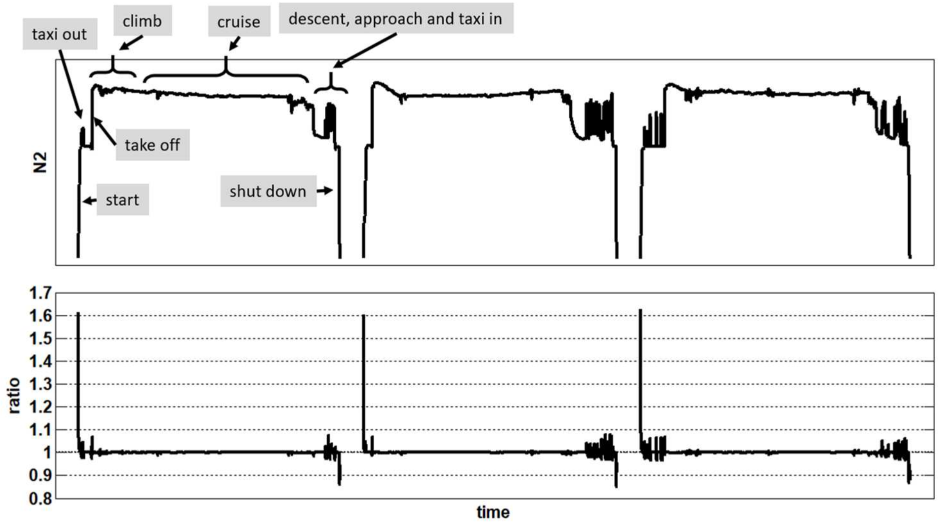

Figure 1: Top: rotation speed profiles N2 of a High Pressure shaft of a civil aircraft engine. Bottom: ratio of the speed at two moments separated by one second.

The spectra on the left of Figure 2 were built when the average speed is at 80% of maximum speed, both in stationary (cruise and approach) and transient (take off and beginning of descent) conditions. For both conditions, one second of raw vibrations is analyzed. For stationary condition, the speed ratio is 1+/-0.0001, while for the transient condition, the speed ratio is in this example 1.063+/-0.002. In the spectra, markers are located at several gear mesh frequencies and harmonics. The spectrum on the right is built when the average speed is at 5% of maximum speed (beginning of an engine start) with a speed ratio of 1.25+/-0.05.

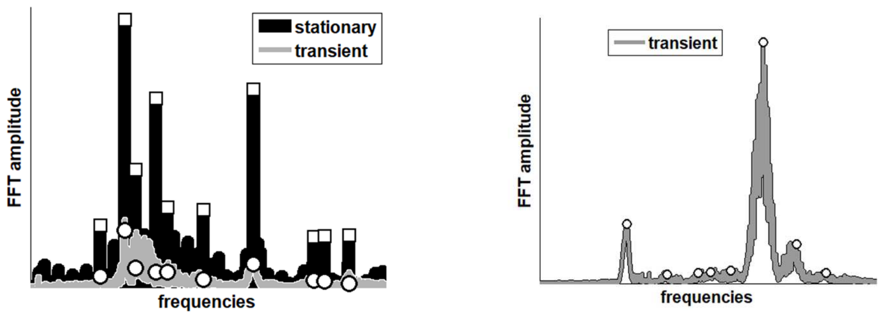

Figure 2: Fast Fourier transform amplitudes of snapshots of one second for different speeds and speed ratios. Left: average speed of 80% of maximum speed. Right: average speed of 5% of maximum speed.

In transient conditions, the energy of the signal is smeared in several frequency bins. This smearing effect can reduce the perfomance of the detection of the relevant peaks at gear mesh frequencies.

In order to make the relevant peaks more salient, the signal should be resampled with the tacholess speed estimation. Such a method is proposed in [2], but this method is limited to small speed variation and it needs a first estimation of the speed. We propose a method based on a simple assumption on the evolution of the speed to overcome this limitation. This method is a very simplified and straightforward version of methods based on time-frequency resolution enhancement such as the more generalized method proposed for instance in [3].

2 A solution to facilitate the speed estimation during strong transients

The main idea is to make the assumption that in a short period of time, the speed varies linearly. This assumption is approximately valid if the duration is short enough and if the rotating shaft has a sufficent inertia relatively to the dynamics of the driving and braking sources of power. Based on this assumption, the signal can be synchronously resampled with a multiple of the rotation speed, without knowing the rotation speed, in order to sharpen the peaks in the spectrum.

We need to find the ratio $R = N_{end}/N_{beginning}$ where $N_{beginning}$ is the speed at the beginning of the time duration, and N_{end} is the rotation speed at the end of the duration, without any idea of $N_{beginning}$ and N_{end}.

In order to find this ratio R, we propose to successively:

- assume a value for R (for instance, arbitrarely chosen as a first guess at the beginning of the process),
- resample the signal with this assumption on R,
- compute the spectrum of the resampled signal,
- sum up the spectrum with a scalar S (for instance, the maximum amplitude of the spectrum, or the sum of the amplitudes of the spectrum as it will be described later in this paper).

The idea is that the ratio R will be found when the scalar S is an extremum if S is appropriately defined. For instance, if S is the maximum amplitude of the spectrum, the ratio R will be found for the argument of the maximum of S. If S is the sum of the amplitudes of the spectrum, the ratio R will be found for the argument of the minimum of S.

We need first to explain how to resample a signal with the knowledge of R and without any other knwoledge on the speed.

2.1 Synchronous resampling with the knowledge of R: the temporal companding

Assume that the vibraton signal is sampled at a constant sampling frequency F_s.

Consider a duration of (K+1) consecutive samples, the original timestamps are $t = n/F_s$ with $n \in [0{:}1{:}K]$.

We assume that during this short duration of time, the rotation speed N varies linearly from $N_{beginning}$ to $N_{end} = R\, N_{beginning}$, where R is the ratio of the speed between the end and the beginning of the duration.

Since we actually just need the shape of N, we can assume a virtual and normalized rotation speed N with a mean value of 1 during this short duration. The formula for the hypothetical virtual and normalized rotation speed N can be expressed solely with the ratio R and is given in Figure 3 where only R remains as an unknown.

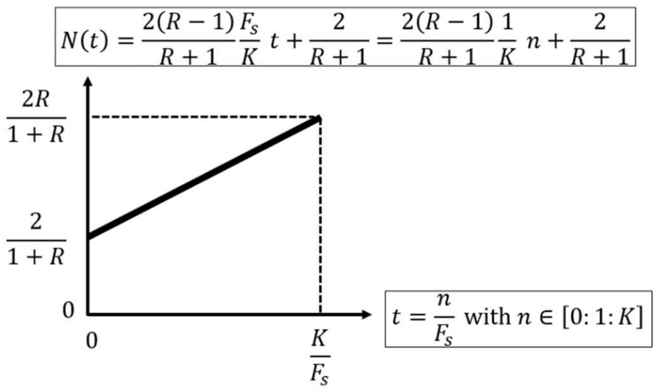

Figure 2: The assumption that the evolution of the rotation speed varies locally linearly with time, and the equation of the hypothetical virtual and normalized rotation speed N.

Once a value of R has been chosen, it is possible to resample the signal synchronously with the unkown virtual and normalized rotation speed N with the following process (see Figure 4):

- Compute the hypothetical phase φ(t), integral of the hypothetical virtual and normalized rotation speed N. Since N is a segment of line, the hypothetical phase is a portion of a parabola that can be expressed with the unknown R.
- Divide the phase axis φ(t) in (K+1) regularly spaced samples. Actually, the number of regularly spaced samples in the phase axis can be chosen arbitrarely with the following considerations:
  - If this number is high enough, we can avoid any downsampling of the original signal.
  - If this number is too low, we can expect to introduce aliasing if the signal is downsampled.
  - For a number of (K+1) samples, half of the signal is upsampled and the other half of the signal is downsampled. This is this case that has been chosen for an embedded system because in this case, the number of samples remains always the same (and it is also the number of samples of the original signal). For an embedded system, it is of great benefit to keep a constant and known number of samples for memory pre-allocation. In this case and in order to avoid any aliasing effect, we shall consider the minimal and maximal expected value of R and apply an anti-aliasing filter of the original signal at the beginning of the process.
- Find the new timestamps t_{new} that are the solution of the reciprocal function of the portion of parabola φ(t).
- Resample the signal on the new timestamps t_{new}, for instance with a simple linear interpolation.

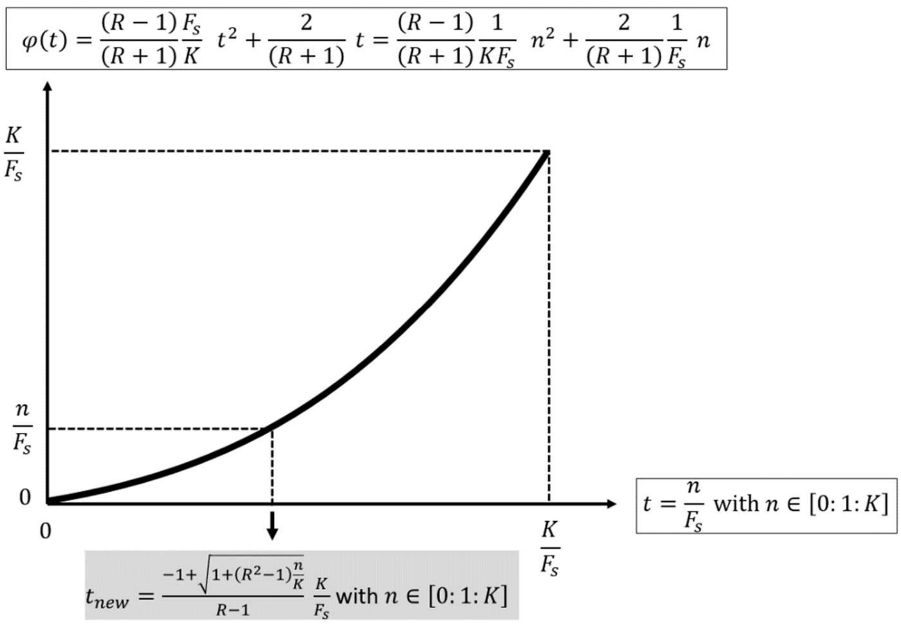

Figure 4: The evolution of the phase φ(t), and the resulting new timestamps t_{new}.

Note that for a ratio R=1, the evaluation of t_{new} is not possible because of a division by zero. This particular case corresponds to the situation where the rotation speed is constant. This particular case shall be considered before applying the process to find R:

- We can make a simple test on the signal to check that the rotation speed doesn't seem to be constant.
- Alternatively, while evaluating the most probable value for R, we should always avoid the evaluation of R=1.

2.2 Finding R

There is many ways to find the most probable value for R. In this paper we will describe an optimization method that seems to be easily compliant with the constraints of an embedded system.

2.2.1 Choosing a parameter for the identification of R

First, we should find an appropriate scalar S for the identification of R. It is assumed that when a signal is mainly composed of energy at harmonic frequencies of a rotation speed, if the speed varies and if the signal is resampled synchronously with the rotation speed, the energy will be concentrated in narrow bands of frequencies with higher amplitudes (the energy is less smeared if the signal is appropriately resampled).

We have analyzed two kinds of properties of the Fourier transform of the signal:

- $S=S_{max}$ as the maximum amplitude of the spectrum, without any consideration on the frequency location of this maximum.
- $S=S_{sum}$ as the sum of the amplitudes of the spectrum (or the mean of the amplitudes, or the area below the spectrum). For the author of this paper, it is not clear why this parameter seems to have the property to be the minimum when the signal is appropriately resampled.

A simulation has been made for a better understanding of the behaviors of those two parameters S.

The simulated signal is a chirp with the following characteristics:

- duration of the signal is 1 s (frequency resolution is therefore 1 Hz),
- sampling frequency is Fs = 32768 Hz,
- amplitude is 1.2 peak (for instance, for an acceleration, 1.2 m/s² peak),
- R = 1.8,
- the signal frequency begins at 2 x 79.3 / (1+R) =56.6429 Hz and ends at 2R x 79.3 / (1+R) =101.9571 Hz,
- phase at t = 0 s is 0°,

A Fourier transform is done on the whole duration of the signal, after apodization with a Hanning window. In order to understand the behavior of S_{max} and S_{sum}, another Fourier transform has been done after zero-padding the signal with 9 time the length of the signal with zeros.

In order to facilitate the comparison of the two parameters S_{max} and S_{sum}, we propose to analyze S_{max_n} and S_{sum_n} where S_{max_n} is a normalization of $-S_{max}$ between 0 and 1, and S_{sum_n} is a normalization of S_{sum} between 0 and 1. In Figure 5 are the evolutions of S_{max_n} and S_{sum_n} when the temporal companding is applied for different hypothetical values of R by step of 0.01. Without zero-padding, the evolution of S_{max_n} seems to be less convex compared to the evolution of S_{sum_n}. Moreover, the argument of the minimum of S_{max_n} is not exactly 1.8. A first explanation is that even if the hypothetical R is close to the real R, the energy is usually smeared in several frequency bins, as it is shown in Figure 6.

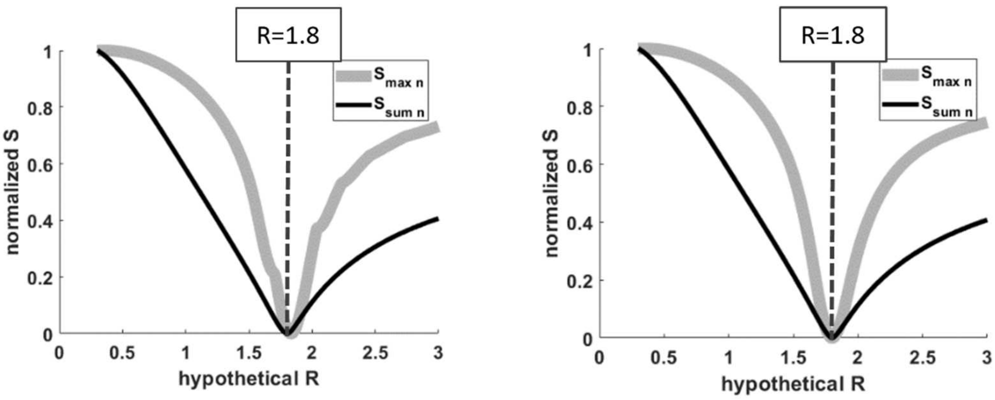

Figure 5: Evolution of S_{max} and S_{sum} with hypothetical R for the simulated signal with R = 1.8.
Left: without zero-padding. Right: with zero-padding.

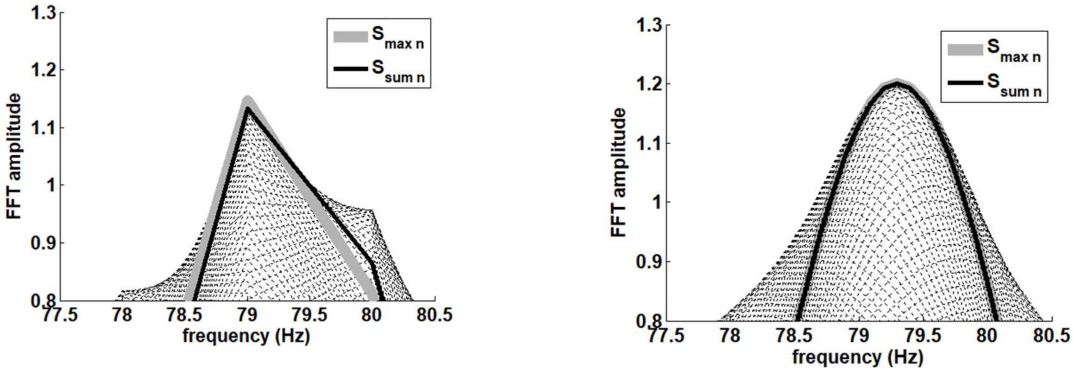

Figure 6: Fourier transform amplitude of the simulated signal with R = 1.8.
Gray dashed lines: results after companding with a grid of hypothetical R values.
Full lines: results after companding with the arguments of the minimum of S_{max_n} and S_{sum_n}.
Left: without zero-padding. Right: with zero-padding.

Finally, in Figure 7 are plotted the relative error of the argument of the minimum for simulated signals with several R. This error is drastically reduced with zero-padding, especially for of S_{max_n}.

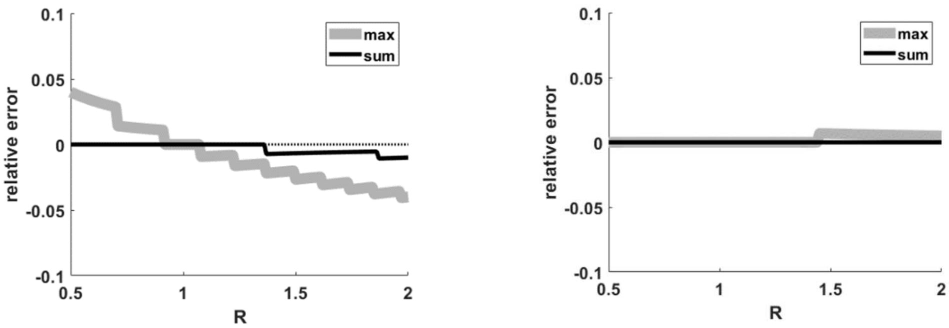

Figure 7: Relative error between R used for the simulation and R as the argument of the minimum.
Left: without zero-padding. Rigth: with zero-padding.

Of course, it is possible that other properties, or combinations of properties of the spectrum could be used to define a good candidate for the identification of R. This study has not been conducted yet.

For the remainder of this paper, and since zero-padding is not a good option for an embedded real time signal processing unit, we have adopted S= S_{sum} because of the apparently good properties of its resulting cost function, even without zero-padding.

2.2.2 Identifying R

It is not a main objective of this paper to propose the best optimization process to find R, but rather an opportunity to take into account the constraints of an embedded system. Among several optimization processes that could be benchmarked are for instance simulated annealing or stochastic gradient descent, eventually with an inertia parameter. Such methods have not been studied here. The optimization method that has been chosen is relatively different and it is based on:

- a discrete grid of potential values for R,
- a kind of dichotomy process.

This latest method has the benefit to be easy to implement in an embedded system. Another benefit is that the process is deterministic and that the maximum number of steps to converge to a solution is fully controlled, which is a great advantage for a real time process.

The drawback is that the solution is clearly not the optimal solution since the possible solutions are trapped in the discrete grid initially proposed. In addition to that, in certain cicumstances, it is possible that the process can converge in a shorter number of iterations than the predefined number of iterations.

It is also possible that the optimization method that best fits the requirement shall be adapted to each particular use case.

In this paper, the study has been made on a single type of civil aircraft engine model. The discrete grid of potential values for R has been defined as R_grid=[0.9:0.001:1-0.001 1+0.001:0.001:1.3]. The range 0.9 to 1.3 has been identified by analysing the rotation speed evolution of several flights (including the engine starts and engine shutdowns). The step of 0.001 has been empirically identified as an appropriate length. Finally, the value of 1 has been excluded from the grid in order to avoid the possible division by 0 when evaluating t_{new}.

The dichotomy process that has been identified as a good candidate for this application is illustrated in figure 8 and consists in the following steps:

- a. Divide R_grid in 2 equal main parts, calculate S at the 3 extremities of the 2 main parts.
- b. Divide each main part in 3 equal sub-parts, calculate 4 new S, and identify for each main part the 2 sub-parts with the lowest S.
- c. Divide each identified sub-parts in 3 equal sub-parts, and identify for each sub-part the 2 sub-parts with the lowest S.
- d. Repeat c until the sub-parts are reduced to 1 point, and consider that the remaining point is the solution.

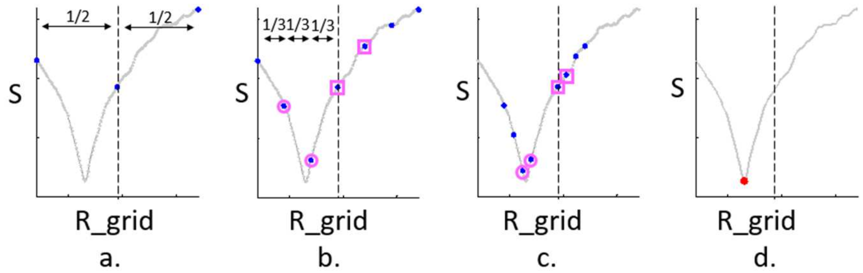

Figure 8: Illustration of the steps for the finding of R.

3 Performances and limitations

3.1 Performances

Figure 9 shows the results of the application of the temporal companding on the data described in chapter 1.3. With the application of the companding technique on the transient signal, several initially smeared peaks are now more salient even if they are of lower amplitudes than the amplitudes in the stationary case. Several peaks are still smeared and barely visible. Indeed, the frequency content and the amplitudes during a strong transient are likely to differ from the frequency content and amplitudes in stationary condition, even at a same average speed.

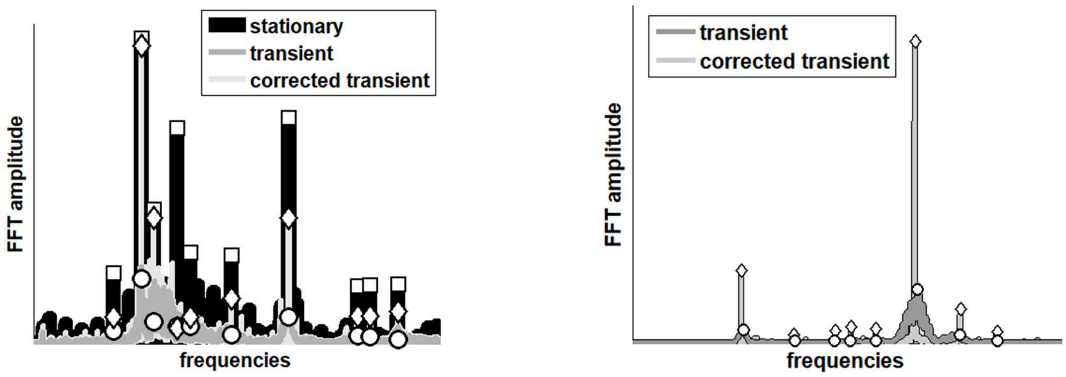

Figure 9: Fast Fourier transform amplitudes of snapshots of one second for different speeds and speed ratios, with the results when the temporal companding is applied on transient conditions.

The performances have been evaluated on a database of several hours of portions of flights with strong transients. Figure 10 shows the evolution of the speed selected for this database.

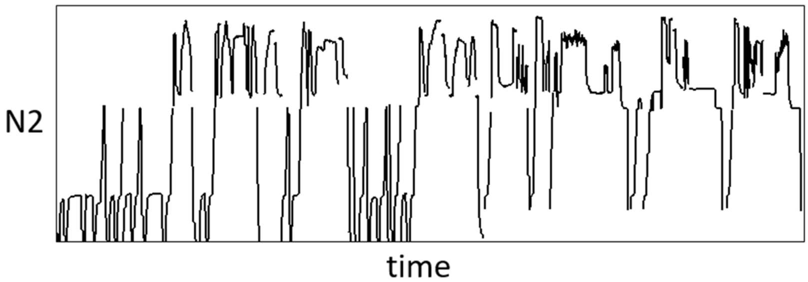

Figure 10: Time history of the speed selected for the database.

The identification of the speed ratio R is exactly correct in 70% cases, and 25% of the incorrect cases are off by only 0.001 (i.e. the step of the chosen R_grid), which are very good results.

Besides those results, an advantage of the proposed method is that the new timestamps can be computed directly for each R because they are the solutions of the reciprocal function of the portion of a parabola.

Another advantage is that we only have to consider a single parameter, R, for the optimization process. We could add other parameters for the local modelisation of the shape of N. For instance, we could have defined a bilinear model composed of 2 linear parts, meaning that we would have to consider 2 ratios and the location of the change of slope, therefore we would have 3 parameters to be taken into account. Another extended modelisation could be that the rotation speed varies with a polynomial shape of higher degree than the linear shape that is proposed in this paper. For instance, for a polynomial of degree 2, we would have to identify 2 parameters that describe a virtual normalized rotation speed. The difficulty is that the size of the domain to explore for the optimization tends to increase dracstically with the number of parameters.

3.2 Limitations

Even if the temporal companding seems to be beneficial for speed estimation, several limitations have been already identified:

- The assumption that the rotation speed varies locally linearly is not true in the general case. This assumption is approximately true for mechanical systems with relatively high mechanical inertia, and for a specific range of duration. For an aircraft engine, it is obvious that this assumption is likely to be false as the duration increases by more than several seconds, for instance at the transition between the end of the starting phase and the beginning of taxi out. It is less obvious that the assumption is true for small durations if the speed presents fast fluctuations, for instance fluctuations caused by an excited torsion mode.
- The temporal companding may be useful for strong transients, it is less appropriate for soft transients. A solution could be to identify that a transient is sufficiently strong with a simpler method than the temporal companding, for instance with a comparison of the frequency content at the beginning and at the end of the duration.
- The method has been tested in the particular case of a single main source of excitations, i.e. all excitations are synchronous with multiples of a speed. The method must be adapted for the cases of multiple sources of excitations which are not synchronous with each other, for instance with the consideration of several portions of the spectrum instead of the consideration of the whole spectrum.

4 Conclusion

A new Health Monitoring system, for the diagnostic of the bearings and gears of an aircraft engine and its equipments, has been described. For this new system, several new constraints arised, among which the need for tacholess speed estimation. We focused specifically on the issue of tacholess speed estimation during strong transients, when speed variation is large. A simple and yet effective preprocessing method, the temporal companding, aims at facilitating the speed estimation during such strong transients. This preprocessing method benefits from properties of the spectrum that are correlated with the instantaneous speed variation. The method also takes advantage of the possibility to sharpen smeared peaks of the spectrum by resampling the signal with a simple assumption on the shape of the unknown rotation speed.

The method has been applied on a signal recorded during several flights on the accessory gearbox of an aircraft engine, and the results are very promising.

Further analysis could be done with the consideration of the whole processing of speed estimation: temporal companding could be applied as a preprocessing method. Another area of investigation is the case of a signal recorded on an aircraft engine, since most aircraft engine applications have several shafts that are not synchronous with each other, and since each shaft is a source of excitations.

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