Time frequency analysis and event detection in noise signals

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Abstract

Linear time frequency analysis is employed for event detection in transportation noise signals and condition monitoring of marine diesel engines. Detected events in transportation noise signals are analysed in the time frequency domain and narrow band components of the signal are calculated in order to extract event types. In marine diesel engines shaft torque signals are monitored using the concept of a localised analysis in time and frequency to identify cylinder misfires. Local analysis is performed using a recursive implementation of the short-time Fourier transform.

1 Introduction

Fourier analysis provides the classical tool for decomposing signals in the frequency domain. However, many real world signals demonstrate non-stationarity and the use of the time or frequency domain individually has limitations. Time frequency methods analyse the two domains jointly and thus give the ability to describe time variable and frequency dependent characteristics of non-stationary signals. In this work time frequency methods are discussed for the detection of events in traffic noise signals and condition monitoring of marine diesel engines.

Detection of events is of vital importance for the detection of faults and the condition monitoring of rotating machinery. In the literature many methods have been proposed for this purpose. Traditional methods make use of cepstrum and waveform analysis [1-2]. Vibration signals however demonstrate non-stationarity and hence more elegant techniques based on time-frequency analysis have been developed. These techniques are based on the assumption that a non-stationary signal can be treated as the sum of consecutive quasi-stationary segments, where stationary classical Fourier transform based methods can be applied.

Staszewski and Tomlinson used a moving window procedure to identify series of impulses in vibration signals and detect a broken tooth in a spur gear [3]. They also demonstrated how different window function parameters affect the results. Wavelet analysis has been employed by Wang to detect transients in mechanical systems [4]. McFadden et al. used a variant of the wavelet transform, the generalised S transform, which allows calculation of the instantaneous phase of a signal and they applied this transform in mechanical systems for the early detection of failure [5].

Quadratic time frequency distributions have also been used. The first to be introduced and the most widely used in practice is the Wigner-Ville distribution (WVD). Improvements of the WVD include the smoothed-WVD [6] and the weighted-WVD [7]. Staszewski et al. proposed the application of statistical and neural pattern recognition to the WVD for condition monitoring of gearboxes [8]. Williams and Zalubas proposed an improved and generalized version of the exponential distribution of Choi and Williams and they showed that it overcomes several drawbacks of the spectrogram and the Wigner-Ville distribution [9]. Other approaches to condition monitoring and fault detection include the use of higher order statistics [10-11] and non-linear diagnostic methods [12].

In this work linear time frequency analysis is used because it is simple to implement and provides means of synthesis and simulation of non-stationary systems. In particular we employ a recursive algorithm for the evaluation of the short time Fourier transform, which is faster compared to non-recursive realisations. The method proposed in this paper is implemented recursively using filter banks. This recursive approach provides the potential of real time implementation in hardware. Use of the developed system is demonstrated in the context of two applications.

In the first application condition monitoring of marine diesel engines is performed. Shaft torque signals are representative of the processes in the engine and detected events indicate healthy or ill operation. Analysis of shaft torque signals in the time frequency domain is used to detect cylinder misfires.

In the second application a method for the automatic detection of events in traffic noise signals is proposed. The fluctuations of the energy of the signal are used as an index to where an event occurs. The values of background noise and fluctuation of narrow band components of the signal are calculated in order to extract event types using variable time intervals. Detection of events was also performed in railway noise signals.

2 Time frequency analysis

2.1 Short time Fourier transform

The short time Fourier transform (STFT) of signal x(t) is defined as

$$X(t,f)=\int_{-\infty}^{+\infty} x(t')w(t'-t)e^{-j2\pi ft'}dt' \quad (1)$$

where w(t) is a window function. Thus the short time Fourier transform is the Fourier transform of the windowed signal and is a function of frequency f and the window position t. The spectrogram is defined as the square of the magnitude of the short time Fourier transform.

Short time Fourier transform demonstrates shift invariance in time and frequency. Thus for a signal $x(t)$ with short time Fourier transform $X(t,f)$ it is

$$x(t-t_0) \leftrightarrow X(t-t_0,f) \quad (2)$$

$$x(t)e^{j2\pi f_0 t} \leftrightarrow X(t,f-f_0) \quad (3)$$

Short time Fourier transform also possesses the properties of reality and positivity and is free of interference terms in case of multi-component signals [13].

2.2 Recursive realisation

The method for the evaluation of the short time Fourier transform used in this work follows Papoulis [14], who proposed a recursive digital implementation of a rectangular window short time Fourier transform. The running Fourier transform of a signal has been defined as the integral

$$F_x(t,\omega)=\int_{-c}^{+c} x(t+\tau)e^{-j\omega\tau}d\tau \quad (4)$$

with the inversion formula

$$x(t)=\frac{1}{2c}\sum_{m=-\infty}^{\infty} F_x(t,m\omega_0),\ \omega_0=\frac{\pi}{c} \quad (5)$$

where c is a given constant describing the limits of the segment of analysis for a fixed t. F(t,ω) are the Fourier transformation coefficients, with respect to τ, of the segment x(t+τ), of x(t), where $-c \le t \le c$. The above definition has been chosen because it leads to a recursive formulation. The evaluation of the spectrogram directly from this expression requires computation of the Fourier transform at any time instant t. It can be proved that $F(t,m\omega_0)$ satisfies the first order differential equation.

$$\frac{dF_x(t,m\omega_0)}{dt}-jm\omega_0F_x(t,m\omega_0)=(-1)^m[x(t+c)-x(t-c)] \quad (6)$$

In order to reduce the computation time, F_x can be evaluated recursively.

Implementing in discrete time, the running z-transform is defined as the short time z-transform of a delayed signal. For a sequence x(n), the running z-transform is:

$$\Phi(n,z)=\sum_{k=0}^{N-1} x(n-k)z^{-k} \quad (7)$$

For fixed n, Φ(n,z) is the z-transform in the variable k of the segment x(n-k) of x(n). The inversion formula, considering evaluation on the unit circle, is

$$x(n)=\frac{1}{N}\sum_{m=0}^{N-1}\Phi(n,w^{-m}) \quad (8)$$

where $w = e^{j\frac{2\pi}{N}}$.

Hence, the running z-transform is the sampled version of the Fourier transform of a delayed sequence x(n-k). For simplicity the above formulation assumes a rectangular window function applied to the signal:

$$g(n) = \begin{cases} 1 & for \quad 0 \le n \le N-1 \\ 0 & elsewhere \end{cases}$$

Substituting k+1=p in (7), results in

$$\Phi(n-1, z) = z\sum_{p=1}^{N} x(n-p)z^{-p} \qquad (9)$$

It follows that function $\Phi(n, z)$ satisfies the first order recursion equation

$$\Phi(n,z) - z^{-1}\Phi(n-1,z) = x(n) - z^{-N}x(n-N) \; (10)$$

and with $z = w^{-m}$, function $\Phi(n, w^{-m})$ follows the simple recursion:

$$\Phi(n, w^{-m}) - w^{m}\Phi(n-1, w^{-m}) = x(n) - x(n-N) \; (11)$$

Equation (11) defines a discrete recursive system with input x(n), output $\Phi(n, w^{-m})$ and system function

$$S(m,z) = \frac{1-z^{-N}}{1-w^{m}z^{-1}}$$

(12)

The system consists of one shift register with output x(n-N), one delay element and one multiplier (Fig. 1). Connecting N such systems together in parallel, results in a running Discrete Fourier Series (DFS) spectrum analyser which can be realised using filter bank structure (Fig. 2).

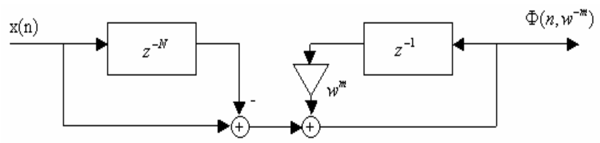

Figure 1: Elementary filter structure.

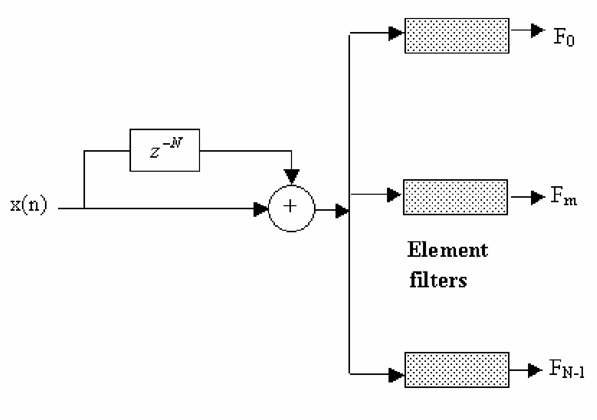

Figure 2: Recursive DFS analyser.

3 Condition monitoring of marine diesel engines

Marine diesel engine monitoring and diagnostics is becoming of increasing interest, due to the introduction of advanced sensing capabilities to modern ship propulsion plants. A quite frequent malfunction of large marine engines is one or more cylinder misfires; such an event may occur as a result of injector failure, fuel system failure (fuel pump, camshaft etc.). Cylinder misfires causes engine brake power and torque reduction and, possibly, shafting system resonance and mechanical overloading; therefore, manners of reliable and well-timed detection are of importance in marine practice, for increasing the safety level of vessel propulsion system operation.

In the specific application, the possibility to detect a single cylinder misfire, by employing linear time frequency analysis, is examined. It is assumed that in-cycle temporal evolution of shaft torque is available in real-time. This assumption is realistic for modern marine plants, as commonly, torque sensing devices based on strain gauge bridges are attached to the engine-propeller shaft. Here, it should also be noted out that shaft torque coincides with engine torque delivery only under steady-state loading conditions; indeed, under dynamic, transient conditions the effect of shaft dynamics should also be included in the analysis.

In the test case demonstrated, the engine torque delivery of the 4T50MX MAN-B&W engine, installed at the Intelligent Engine testbed at Copenhagen, Denmark, is plotted for a steady-state cycle of the engine for the cases of normal operation and with a single cylinder misfire (Fig. 3). The data series were generated by a detailed thermodynamic engine simulation tool. As can be seen, the data series are plotted with respect of crank angle and not of time. This is preferable because, the pattern observed (that can be roughly approximated by a sine wave) is maintained over the entire operating range of engine speed (rpm), with the same fundamental harmonic. The fundamental harmonic in the case of the 4T50MX engine, which is a 4-cylinder, 2-stroke engine is $360^O/4 = 90^O$. In any case, the plots can be readily transformed to time bases if the crank angle value is divided by engine speed expressed in deg/s.

The recursive implementation of the Fourier transform is used for the detection of the malfunction. Assuming the speed of engine to be 100 rpm, the shaft torque signal for the steady-state normal cycle of the engine is decomposed in the time frequency plane, using a rectangular window of one engine cycle width (Fig. 4). The harmonic structure of the signal is preserved throughout the cycle.

In Fig. 5 the time frequency analysis of the shaft torque for a cycle with a single cylinder misfire is presented. The malfunction is detected as the breakdown of the harmonic structure of the signal. Having used an analysis window of one cylinder width the faulty cylinder is easily located to be the second one. A different analysis window may complicate the location procedure, but better time or frequency resolution can be achieved.

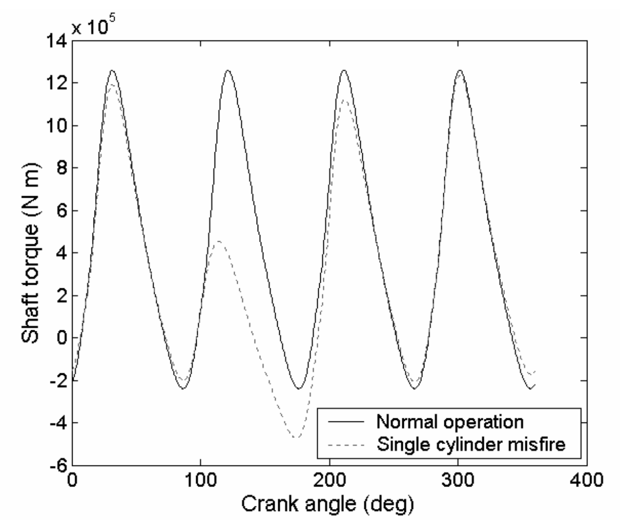

Figure 3: Engine torque delivery for steady-state cycle of the engine.

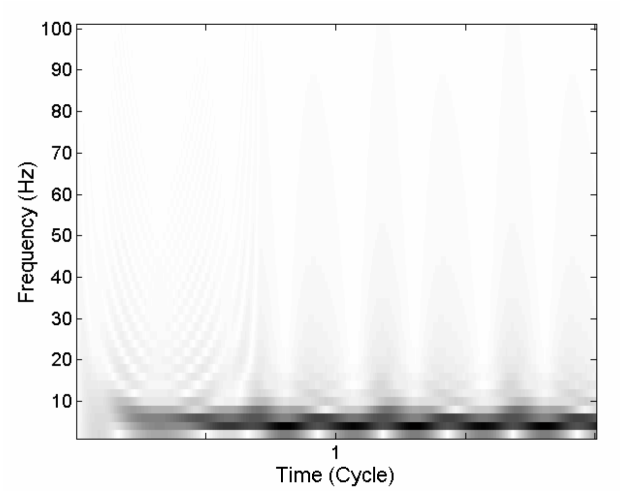

Figure 4: Time frequency analysis of the shaft torque for a steady-state normal cycle.

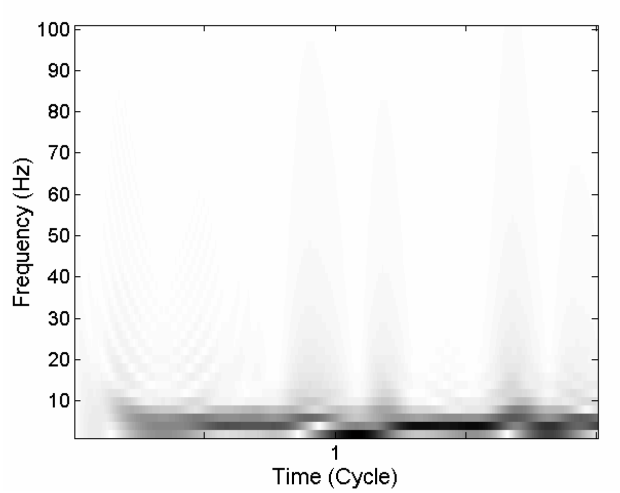

Figure 5: Time frequency analysis of the shaft torque for a steady-state cycle with a single cylinder misfire.

4 Transportation noise event detection

The disturbance caused by transportation noise is highly associated with the number, amplitude and frequency content of noise events [15]. Noise events are detected in the time domain using the fluctuations of the energy of the signal as an index to where an event occurs. Events are defined as having double energy of the background noise. The values of background noise are calculated using variable time intervals.

Event detection in transportation noise signals is usually employed to evaluate sleep disturbance. Sleep disturbance caused by transportation noise includes increased sleep latency, shorter duration of sleep, increased number of awakenings and abnormal shifts in sleep stages resulting in symptoms such as tiredness and slow reaction for the person. According to Horonjeff et al. it is probable the difference between the background noise level and event noise levels rather than the absolute event level that is of importance for awakenings [16]. Following this approach the difference between the level of the detected events and the background noise level is calculated.

Detected events are decomposed in the time frequency domain and narrow band components of the signal are calculated in order to extract event types. In Fig. 5 the time frequency analysis of a train horn noise event is shown. The event was detected in a traffic noise signal. The sampling frequency is 11025 Hz and the signal is analysed using a rectangular window of 512 points length. The harmonic structure of the signal is clearly shown.

The described methodology does not depend on the use of A-weighted equivalent continuous sound level (L(A)eq) as a single index for the evaluation of transportation noise disturbance. Instead it proposes the use of the number of events and the difference between the event noise level and the background noise level as independent variables. Moreover, the type of event, identified by time frequency analysis as harmonic, broadband or narrow band, is taken into account.

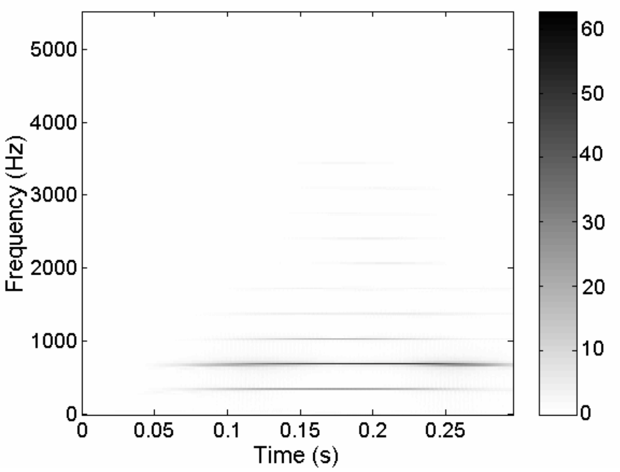

Figure 5: Time frequency analysis of train horn.

5 Conclusion

In this work the short time Fourier transform is used for condition monitoring of marine diesel engines and for the event detection and disturbance assessment of transportation noise. The short time Fourier transform is evaluated recursively, using a methodology, which is faster when compared to non-recursive realisations, and provides the potential of real time implementation in hardware. The recursive realisation is performed using filter banks.

In marine diesel engines operating under steady-state loading conditions linear time frequency methods can be used for condition monitoring. In this work a recursive implementation of the short time Fourier transform was used to detect a single cylinder misfire with success.

For the assessment of transportation noise disturbance we propose the use of the number of events and the difference between the event noise level and the background noise level as independent variables. Detection of events is based on the fluctuations of the energy of the signal. Detected events are analysed using time frequency methods and events are identified as harmonic, broadband or narrow band. The relation between different types of noise events and the caused disturbance should be further investigated.

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