

Chapter 8

Detection of Patterns in Pressure Signal of Compressed Air System Using Wavelet Transform



Mohamad Thabet, David Sanders, and Nils Bausch

Abstract This paper investigates detecting patterns in the pressure signal of a compressed air system (CAS) with a load/unload control using a wavelet transform. The pressure signal of a CAS carries useful information about operational events. These events form patterns that can be used as ‘signatures’ for event detection. Such patterns are not always apparent in the time domain and hence the signal was transformed to the time-frequency domain. Three different CAS operating modes were considered: idle, tool activation and faulty. The wavelet transforms of the CAS pressure signal reveal unique features to identify events within each mode. Future work will investigate creating machine learning tools for that utilize these features for fault detection in CAS.

Keywords Compressed · Air · Systems · Intelligent · Wavelet

8.1 Introduction and Literature Review

This paper investigates detection of patterns in CAS pressure signal using a continuous wavelet transform (WT). CAS pressure signal characteristics that make WT a suitable analysis tool are discussed. Then, experiments performed and results obtained after applying WT are presented. Matlab function ‘cwt’ was used to apply WT. Results confirm that applying WT on a CAS pressure signal reveals unique patterns that can be used for fault detection.

Running a Compressed Air System (CAS) has a high energy cost [1, 2] and the efficiency of many CAS could be improved. Innovations in intelligent systems for automatic energy consumption control and fault detection might help address CAS energy efficiency [3].

Section 8.2 considers the CAS pressure signal, Sect. 8.3 presents the experiment and results and Sect. 8.4 concludes the paper.

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8.2 Compressed Air Pressure Signal

A CAS pressure signal contains patterns that may be associated with operational events. Events, such as a compressor turning on or off in system with load/unload control, could be detected directly from the time domain pressure signal. However, detecting other events, such as tool or filter activation, was not as straightforward. In such cases, transforming the pressure signal to the frequency domain revealed features to recognise these events. The CAS pressure signal is non-stationary. For non-stationary signals, a Fourier transform provides information about frequency content, but not about time localization of those frequencies. A time-frequency signal processing tool, such as the WT, is more suitable for analysing a load/unload CAS pressure signal. A similar attempt to analyse a CAS pressure signal with WT was investigated in [4].

8.3 Experiments and Results

The industrial CAS installed in the University of Portsmouth was used for data collection. A pressure sensor was connected to the piping network and an air gun was used to simulate a tool activation. Data was recorded at a rate of 1 sample per second. The compressor had load/unload control, so the compressor turned on when the tank reached the lowest pressure limit and off when it reached the upper pressure limit. Three different scenarios were considered. The first corresponded to the case where no tool was activated (referred to as idle case). In the second case, an air gun was activated to simulate a tool activation. Finally, the third case corresponded to data recorded when the system had a leaking filter and different compressor control pressure limits. Each of these cases are analysed.

8.3.1 Idle Case

In the idle case compressed air consumption was due to small leaks in the system. Figure 8.1 shows pressure variation in this case. Pressure variation was obtained by removing the mean from the recorded data. The compressor switched on when the system pressure decreased by ~ 0.15 bar leading to a rapid increase in system pressure. Once the compressor switched off, the pressure decreased slowly. While the compressor was off, events such as filter activation, led to an increased loss in system pressure, reflected as a steeper decrease in pressure.

The WT of the idle signal is shown as a 3D contour plot in Fig. 8.2. On the z-axis, coefficient magnitude instead of coefficient are plotted to make visualization easier. Low frequency components (~ 0.01 Hz) had the highest coefficient magnitude and were present at all times. These components corresponded to the overall saw

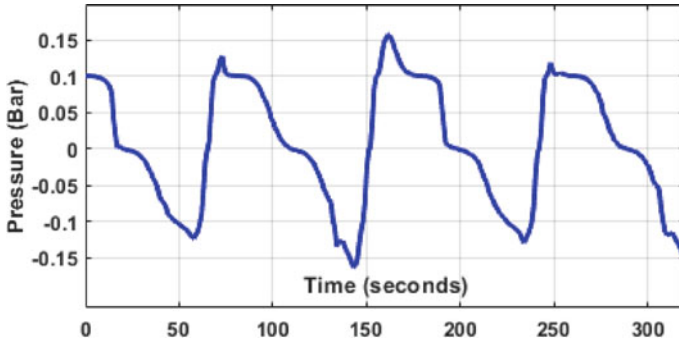


Fig. 8.1 Pressure signal change for the idle case

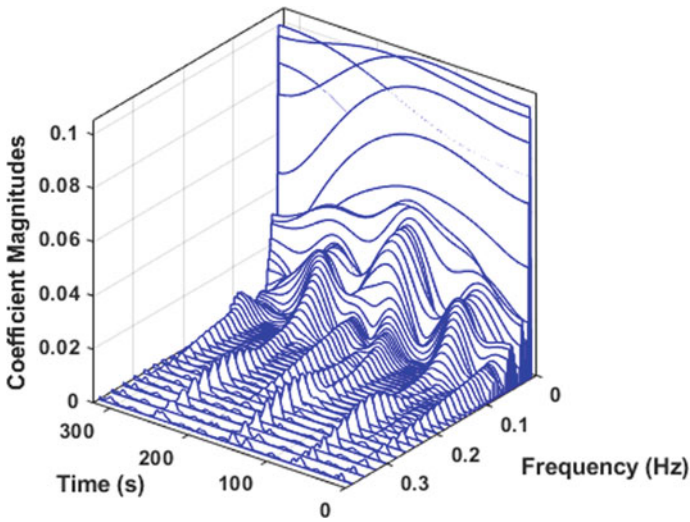


Fig. 8.2 Wavelet transform 3D contour plot for the idle case

tooth pattern of the signal (period of 100 s and frequency of 0.01 Hz). Compressor switching on introduced higher frequency components identifiable on the WT plot. These components had peaks (of different magnitudes) at frequencies of 0.05 and 0.25 Hz, both disappearing after the compressor switched off. Filter activation generated patterns with a peak at a frequency of 0.05 Hz.

8.3.2 Tool Activation Case

An air gun was used to study the impact of a tool activation. Compared to the idle case tool activation, while the compressor was on, led to longer compressor running times before the upper pressure limit was reached. Tool activation while the compressor was off increased the rate of air discharge, which accelerated pressure decrease so that the system reached the lower pressure limit faster. Figures 8.3 shows a pressure change while the air gun was on.

The WT of the tool activation signal is shown in Fig. 8.4. The plot reveals two patterns of interest. The first is the coefficients at frequencies of 0.05 Hz, and the second pattern is the coefficients at frequency range of 0.1–0.2 Hz. Both of these patterns were present at almost all times, unlike the idle case in which these frequencies only appeared when the compressor was on or when a filter was activated. While

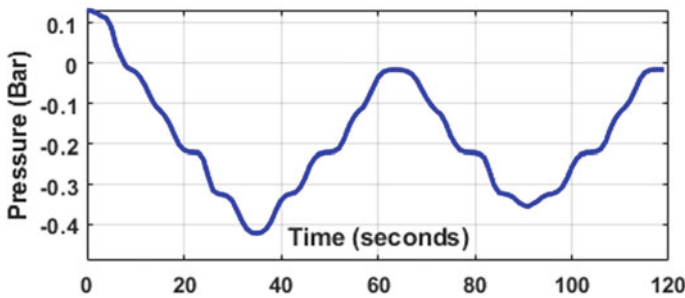


Fig. 8.3 Pressure signal change for tool activation

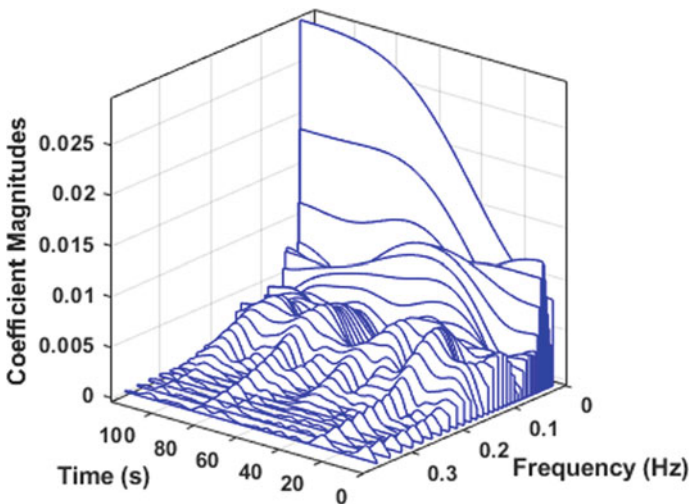


Fig. 8.4 Wavelet transform 3D contour plot for the tool activation case

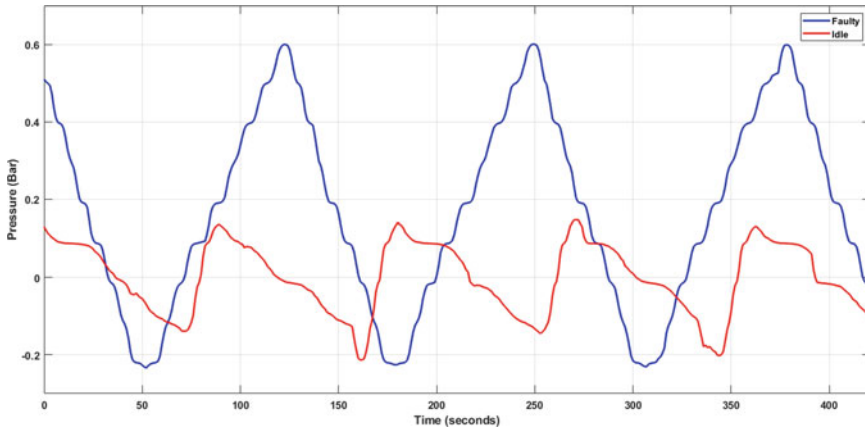


Fig. 8.5 Pressure change for a faulty system. The idle pressure signal shown in Fig. 8.3 is also shown for comparison

the tool was activated, compressor charging and discharging in the time domain signal had relatively similar slopes. This led to similar frequency components being present at all times.

8.3.3 *Faulty Case*

Data recorded when the system had two different faults was utilized to analyse faulty behaviour using a wavelet transform. The systems pressure control limits deviated from original settings, pushing the upper pressure limit higher. In addition, one of the filters had a relatively large leak. The pressure change for this case is shown in Fig. 8.5 alongside the idle case for comparison.

Because the upper pressure limit was higher, and due to the leak in the filter, the time the compressor spent on was longer. Moreover, the increased compressed air consumption due to the leak, meant the lower pressure limit was reached faster. The WT of the faulty system signal is shown in Fig. 8.6. Because the amplitude of the signal was relatively high (compared to idle and tool activation cases), the magnitude of the low frequency components was also high (0.14 compared to 0.025 and 0.1 in the idle and tool activation cases). The high frequency spectral components were similar to the ones seen for the tool activation case. This result is expected since a tool activation, such as an air gun, resembles the presence of a leak in the system.

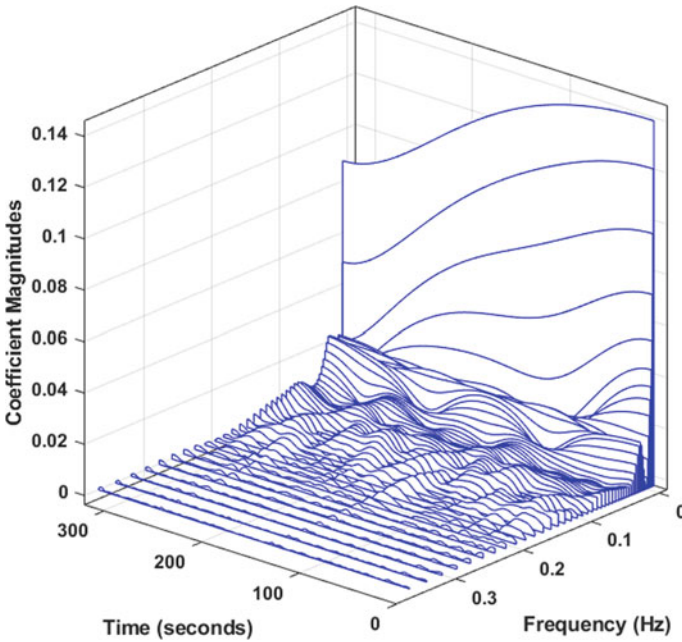


Fig. 8.6 Wavelet transform of a faulty system pressure signal shown in Fig. 8.5

8.4 Conclusion

This paper investigated the suitability of the WT for extracting features from the pressure signal of a CAS. Three different cases were considered: Idle, faulty and tool activation. The analysis proved that it is possible to generate features to identify different events, such as a tool activation and leaks. Future work will investigate employing those features to create a classifier for leak detection.

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