PS-12 音響解析による異常燃焼モニタリング技術に関する研究

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1. Introduction

In gas-fueled engines for marine application, the identification of knock condition onset and the evaluation of its intensity prior to evolving into serious breakdowns are important to ensure efficient, reliable and safe operation.

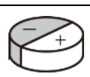
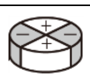
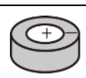
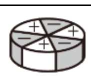
In the recent time Acoustic Emission (AE) based monitoring methods are found applications to internal combustion engines. The applicability has been demonstrated in discriminating the combustion related and mechanical system related components from engine AE even with rather small energy levels. Furthermore, combustion related faults of different severity as well as engine health condition change can be identified from the analysis of the AE signal, also detection of the excessive knock operational regime of engine is possible.

This paper addresses the problem of the knock combustion identification at the early stage by the non-intrusive method such as AE analysis. The recorded acoustic signals from the gas-fueled engine are scrutinized closely with time-frequency analysis and the obtained signal features are compared to those obtained from vibration and in-cylinder pressure signals.

2. Instrumentation and knock property

The test engine used in this study is the mass-produced AYG20L engine designed by Yanmar. For data acquisition, only one cylinder of the test engine was instrumented with sensors: a combustion pressure transducer, a shock sensor on engine block, and a microphone close to engine block at the intake port side. All signals were recorded simultaneously and synchronized with crankshaft position. For knock data acquisition, the engine parameters were tuned to provoke knocking condition of varying severity, thereby providing a vast database for evaluating the AE features with respect to knocking intensity.

Table 1. The knocking modes fundamental frequencies

Mode	 $\alpha_{1,0}$	 $\alpha_{2,0}$	 $\alpha_{0,1}$	 $\alpha_{3,0}$
f, kHz	3.2	5.26	6.6	7.3

The knock phenomenon characterizes abnormal combustion that initiates spontaneously in the combustion chamber of engine and as a result the resonant pressure waves are induced. The frequency at which these waves propagate depends on speed of sound in combustion chamber, cylinder diameter and considered knock mode. The resonant frequencies for the first four modes of the test engine are reported in Table 1 together with graphical representation of the corresponding mode. As discovered by many studies, the main portion of the knock energy is contained within the lowest mode $\alpha_{1,0}$. Last but not least, mode frequency changes with piston position, combustion temperature and composition of the end gas and this indicates on the non-stationary nature of knock event.

3. Knock event classification

The knock event from AE signal could not be discriminated with the frequency information alone, as this event may be buried in other components with similar frequency content, moreover due-to nonstationary nature of knocking a bidimensional time-frequency analysis has to be considered. In this respect a continuous wavelet transform is beneficial and it is defined as inverse Fourier transform of product the Fourier transform of signal and wavelet basis:

$$W_n(s) = \sum_{k=0}^{N-1} \hat{x}_k \hat{\psi}^*(s\omega_k) e^{i\omega_k n\delta t} \tag{1}$$

where $\hat{x}_k$ is the Fourier transform of a data sequence, $\hat{\psi}^*$ is the conjugate of normalized Fourier transform of the Morlet wavelet defined as:

$$\hat{\psi}(s\omega_k) = \left(\frac{2\pi s}{\delta t}\right)^{1/2} \left(\pi^{-1/4} H(\omega_k) e^{-\frac{(s\omega_k - \omega_0)^2}{2}}\right) \tag{2}$$

The wavelet transform defines a joint time-frequency energy density called wavelet power spectrum, denoted by:

$$P_{WT}(n,s) = \left|W_n(s)\right|^2, \quad n \in 0, N-1 \tag{3}$$

After resolving the nonstationary features of data by wavelet transform the knock event can be classified from the moments of discrete density functions provided by the singular value decomposition (SVD) of the wavelet power spectrum. The SVD is defined as:

$$P_{WT} = U\,S\,V^T = \sum_{i=1}^{R} \sigma_i \{P_{WT}\}_i, \quad \therefore \{P_{WT}\}_i = \boldsymbol{u}_i \boldsymbol{v}_i^T \tag{4}$$

where R is the rank, σ_i are the singular values sorted in the descending order and constituting the diagonal matrix S, $\boldsymbol{u}_i$ and $\boldsymbol{v}_i$ are the corresponding singular vectors constituting the matrices U

and V correspondingly. Owing to the orthonormality of the singular vectors $\boldsymbol{u}_i$ and $\boldsymbol{v}_i$, the element-by-element squares of matrices $\{P_{WT}\}_i$ create proper discrete density functions from which a subset of temporal and spectral moments can be obtained:

$$\{t^p\}_i = \sum_{k=1}^{m} (t_k)^p \tilde{\boldsymbol{u}}_i(k); \quad \{f^q\}_i = \sum_{l=1}^{n} (f_l)^q \tilde{\boldsymbol{v}}_i(l)$$
$$\therefore \tilde{\boldsymbol{u}}_i(k) = u_{k,i}^2 \qquad \therefore \tilde{\boldsymbol{v}}_i(l) = v_{l,i}^2 \tag{5}$$

The first moments (p = q = 1) estimate time-correlated instantaneous frequency, and the second moments (p = q = 2) determine the time duration and instantaneous bandwidth for each feature in distribution. Then, each feature can be defined as a 5-element vector:

$$F_i = \left(\tilde{\sigma}_i, \bar{t}_i, \bar{f}_i, \hat{t}_i, \hat{f}_i\right) = \left(\frac{\sigma_i^2}{\max\left(\sigma_i^2\right)}, \{t_i\}, \{f_i\}, \sqrt{\{t^2\}_i - \bar{t}_i^2}, \sqrt{\{f^2\}_i - \bar{f}_i^2}\right) \tag{6}$$

Although the SVD processing provides a suitable tool for features extraction, the SVD may span the entire range of time and frequency with no single energy concentration at any given time or frequency. To overcome this deficiency, a new transformed singular value decomposition (TSVD) method is employed[1)]. The TSVD is defined as:

$$P_{WT} = Y Z X^T = \sum_{i,j} z_{i,j} \boldsymbol{y}_i \boldsymbol{x}_j^T \tag{7}$$

where Y, Z and X are the transformed singular vector and singular value matrices, defined as follow:

$$Y = VD, \quad X = UC, \quad Z = C^T SD \tag{8}$$

where C, D are specific transformation matrices and are found in a way that maximizes the mean of X and Y:

$$E[X] = C^T M_u C, \quad E[Y] = D^T M_v D \tag{9}$$

Figure 1 illustrates how the in-cylinder pressure signal is transformed using the wavelet transform and SVD followed by TSVD techniques. Finally, the features are extracted from the discrete density functions provided by TSVD and features (instantaneous frequencies with the largest energy) distribution obtained from measured signals are reported in figure 2.

4. Conclusions

It was found that knock condition can be detected using AE signal recorded by microphone. The chosen transform yields precise determination of dominant components related to knock fundamental frequencies and features extracted by the wavelet-TSVD technique can be used to classify knock appearance and severity. The last is important for unsupervised monitoring and control of gas-fueled engines.

References

1) Groutage, D. et.al. Advanced Signal Processing Algorithms, Architectures, and Implementations. Volume (4116).

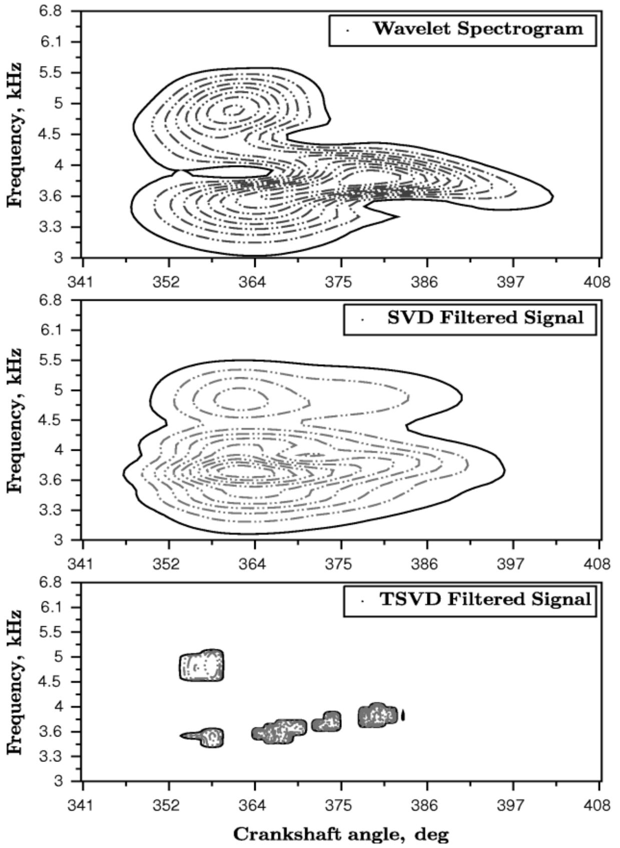


Fig. 1 Time-Frequency analysis of in-cylinder pressure

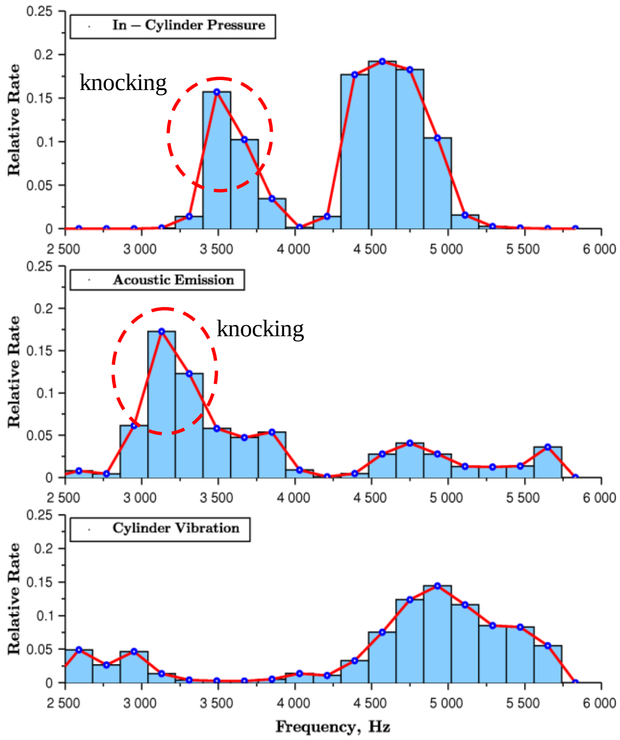


Fig. 2 Distribution of detected features of 1000 consecutive cycles in knocking condition