PRESSURE RECONSTRUCTION AND MISFIRE DETECTION FROM MULTICHANNEL STRUCTURE-BORNE SOUND

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ABSTRACT

Though a variety of misfire detection methods exist, the number of approaches based on structure-borne sound is scarce due to its difficult interpretation. The paper presents a procedure for misfire diagnosis that exploits a multichannel sound signal from accelerometers mounted on the surface of an automotive engine. The EM algorithm is used to decompose the measured sound into individual components associated with single combustions. For these simplified scenarios, a statistical test based on the shape of the reconstructed in-cylinder pressure is devised. Measurement data collected from a four cylinder test bed engine is used to validate the proposed approach and show its superiority to the single-channel solution.

1. INTRODUCTION

Driven by gradually more demanding government regulations, the detection of misfired combustions in automotive engines has attracted considerable interest in recent years. The unsuccessful ignition of the air-fuel mixture inside the cylinders affects the fuel efficiency adversely and has a negative impact on the environment. Therefore, on-board diagnosis systems are required to monitor the combustion process and to alert the driver when the misfire rate exceeds certain mandatory threshold.

The methods proposed in the literature differ primarily in the nature of the signal used for diagnosis. The most extended approaches, which are also the ones usually found in production engines, are based on the analysis of the instantaneous fluctuations in the engine angular velocity [1]. The highly sampled signal from a gear wheel attached to the crankshaft is used to detect the decrease in torque caused by misfired combustions. However, it is often difficult to identify specific faulty cylinders, especially at high speeds, low loads and certain road conditions.

Though standard production engines use one or more built-in accelerometers to detect the occurrence of knock, the literature on the application of these signals to misfire detection is very scarce. Lindemann's approach, which tries to detect the misfire signature using nonlinear polynomial filtering, is one of the exceptions [2].

The method proposed in this paper generalizes the results presented by the authors in [3, 4, 5] for the single channel case. The multichannel sound signal is first processed to obtain an approximation of the individual in-cylinder pressure traces, and then a conceptually simple test function is applied to detect the occurrence of misfire. The goal is to exploit both the redundancy of the multichannel signal and also the complementary perception of the engine cylinders due to the different positions of the accelerometers.

In order to simplify the notation, the paper addresses the signal model for a single structure-borne sound sensor first. The EM algorithm is used to decompose the sound signal into the contributions from the individual combustions. Thus, the EM framework allows to introduce a simplified signal model consisting of a single sound signature plus noise, which can be extended straightforwardly to the multichannel case. The reconstruction of the pressure trace is described as a prior step to the misfire detector, which implicitly uses the estimated pressure shape as criterion. Finally, the performance of the method and its superiority to the single sensor approach are illustrated with real measurement data from a test bed engine.

2. SOUND SIGNAL MODEL FOR A SINGLE SENSOR

The measured structure-borne sound is considered to result from the superposition of N_{cyl} different sound components, one for each cylinder, which are filtered versions of the corresponding pressure signals [3]. The linearity of the filters allows to segment the N_{cyl} signals in the individual combustions, and to reorder them following the ignition order. This way, the measured sound can also be expressed alternatively as the superposition of the contributions of each individual combustion. The model for the structure-born sound from a single accelerometer is then

$$y_n = \sum_{l=-\infty}^{\infty} y_{l,n}(\underline{\vartheta}_l) + w_n, \tag{1}$$

$$y_{l,n}(\underline{\vartheta}_l) = H_{[l]}(q^{-1}, n)\, x_{l,n}(\underline{\vartheta}_l). \tag{2}$$

The left hand side of (1) is actually a filtered version of the raw structure-borne sound signal, $y_n = A(q^{-1})y_n^0$, where q^{-1} is the backward shift operator, i.e. $q^{-m}z_n = z_{n-m}$, and $A(q^{-1}) = 1 + \sum_{m=1}^{M_A} a_m q^{-m}$ is the impulse response of the filter. The term $y_{l,n}(\underline{\vartheta}_l)$ denotes the sound signature of the single pressure trace $x_{l,n}(\underline{\vartheta}_l)$, which is obtained after applying the time-variant filtering $H_{[l]}(q^{-1}, n)$ to the latter. The subscript $[l]$ is shorthand for '(l mod N_{cyl}) + 1', since each combustion is associated with one of the N_{cyl} cylinders and, correspondingly, a specific time-variant transfer function. Finally, the noise term w_n is modelled as a white gaussian stochastic process of unknown variance σ_w^2.

The periodic movement of the piston motivates the use of $H_k(q^{-1}, n)$, $k = 1, \ldots, N_{cyl}$ [3, 6]. Assuming that the piston position $z_{k,n} \in [z_{min}, z_{max}]$ captures the time-variant character of the system, the transfer functions take the form

$$H_k(q^{-1}, n) = H_k^{(0)}(q^{-1}) + z_{k,n} \cdot H_k^{(1)}(q^{-1}). \tag{3}$$

Accordingly, $H_k(\cdot)$ combines two conventional linear time-invariant impulse responses, one of which is modulated by the piston position.

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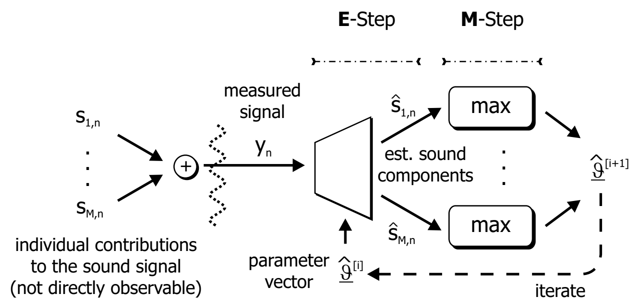

Fig. 1. Symbolic representation of the EM algorithm.

The individual pressure traces are parametrized as proposed in [3]. The pressure due to compression of the fuel mixture and the final phase of the combustion are modelled with one static shape each. A third curve with a position parameter is used to describe a moving lobe. The parametric model for a single combustion is then, as a function of the continuous crank angle γ,

$$x(\underline{\vartheta};\gamma) = \alpha_1 \cdot u(\gamma) + \alpha_2 \cdot v_1(\gamma) + \alpha_3 \cdot v_2(\gamma - \delta), \quad (4)$$

where $\underline{\vartheta} = (\alpha_1, \alpha_2, \alpha_3, \delta)'$ contains the amplitudes and the nonlinear position parameter δ. For a 4-stroke reciprocating engine, $x(\underline{\vartheta};\gamma) = 0$ outside the interval $\gamma \in [-180^\circ, 540^\circ)$ around TDC (top dead center, the top upper piston position), with the main pressure contribution taking place in the first 360° of this interval (compression and power stroke).

3. EM FRAMEWORK

Though in (1) the summation is taken over all combustions, the duration of the sound components is limited in time and thus only a few ones contribute to the sound measured at a certain instant. Consider now the task of estimating the pressure parameters $\underline{\vartheta}_l$ for the l-th component. The relevant data window, of length N_l, is comprised between the starting and ending samples of the l-th combustion. Since the different sound signatures overlap partially, a total of M_l combustions contribute in different degrees to the measurements in the window. Then, arranging the data in the vectors $\underline{y} = (y_1, \ldots, y_{N_l})'$ and $\underline{y}_m(\underline{\vartheta}_m) = (y_{m,1}(\underline{\vartheta}_m), \ldots, y_{m,N_l}(\underline{\vartheta}_m))'$, $m = 1, \ldots, M_l$, an estimate for the interesting parameter vector $\underline{\vartheta}_l$ can be found by solving the least squares problem

$$\min_{\underline{\vartheta}_1,\ldots,\underline{\vartheta}_{M_l}} \left\| \underline{y} - \sum_{m=1}^{M_l} \underline{y}_m(\underline{\vartheta}_m) \right\|^2, \quad (5)$$

where $\|\cdot\|$ represents the Euclidean norm of a vector.

The evaluation of (5) involves a great overhead, since the main interest lies on the parameters of just the l-th combustion. The authors proposed in [3] to use the EM (Estimation - Maximization) algorithm [7] to circumvent the computationally demanding nonlinear multidimensional search for the δ_m's (4) and to exploit estimates from previous data windows efficiently.

The EM algorithm, as depicted in figure 1, uses a prior parameter vector $\hat{\underline{\vartheta}}^{[i]}$ to decompose the measured signal into the individual components. This decomposition transforms the original problem (5) into a set of simpler optimization tasks of reduced dimension that are solved in parallel in the M-Step. Since the algorithm guarantees that the likelihood $L(\hat{\underline{\vartheta}}^{[i+1]})$ for the new parameter vector $\hat{\underline{\vartheta}}^{[i+1]}$ is greater or equal to $L(\hat{\underline{\vartheta}}^{[i]})$, the two-step procedure is iterated until convergence. The reader is refered to [3] for a more detailed description.

3.1. Simplified signal model

The EM framework reduces the original task (5) to a simplified scenario consisting of a single sound signature embedded in noise. The extension of the estimation problem to the multichannel case can then be realized in a straightforward way.

The signals from P accelerometers are combined to obtain better pressure reconstructions and improved misfire detection capability with respect to one sensor alone [4]. The goal is to exploit the strong dependence of the measured sound signal on the physical position of the sensor with respect to the different cylinders.

Contrary to array processing, the geometry of the problem is too complicated to formulate an exact physical relationship between the signals registered by the different accelerometers. The only common property is that the sound signatures, though different from sensor to sensor, are originated by the same combustion.

In the remaining we will refer exclusively to signals associated with the l-th combustion. Therefore, this index will be dropped off the notation for simplicity. On the other hand, the index i is introduced to refer to the different structure-born sound channels. Under this considerations, the signal model for each of the P sensors now satisfies

$$\underline{s}_i = \underline{y}_i(\underline{\vartheta}) + \underline{w}_i, \qquad i = 1, \ldots, P. \quad (6)$$

Within the EM framework, the sound component $\underline{s}_i$ associated with the l-th combustion and the i-th sensor combines a sensor-specific signature of the pressure trace, $\underline{y}_i(\underline{\vartheta})$, and a noise component $\underline{w}_i$. This term, ideally a fraction of the global noise signal for the i-th channel (1), is further modelled as a white gaussian stochastic process with covariance $\mathbf{Q}_i = \mathrm{E}\,\underline{w}_i\underline{w}_i' = \sigma_i^2\mathbf{I}$ and statistical independence between sensors, $\mathrm{E}\,\underline{w}_i\underline{w}_j' = \mathbf{0}$, $i \neq j$.

According to the parametric pressure model (4), the common pressure trace has the form

$$\underline{x}(\underline{\vartheta}) = \alpha_1 \cdot \underline{u} + \alpha_2 \cdot \underline{v}_1 + \alpha_3 \cdot \underline{v}_2(\delta) = \mathbf{X}(\delta) \cdot \underline{\alpha} \quad (7)$$

where $\underline{\alpha} = (\alpha_1, \ldots, \alpha_3)'$ contains the estimated amplitudes, $\underline{u}$ corresponds to the compression curve and both $\underline{v}_1$ and $\underline{v}_2$ describe the pressure increase associated with a successful combustion. The filtering of $\underline{x}$ with the time-variant transfer function $H^i_{[l]}(q^{-1}, n)$ yields the sound signature for a specific combustion and channel

$$\underline{y}_i(\underline{\vartheta}) = \alpha_1 \cdot \tilde{\underline{u}}^i + \alpha_2 \cdot \tilde{\underline{v}}_1^i + \alpha_3 \cdot \tilde{\underline{v}}_2^i(\delta) = \mathbf{Y}_i(\delta) \cdot \underline{\alpha}_i. \quad (8)$$

Finally, with the multichannel vectors $\underline{s} = (\underline{s}_1', \ldots, \underline{s}_P')'$, $\underline{y} = (\underline{y}_1', \ldots, \underline{y}_P')'$, $\underline{w} = (\underline{w}_1', \ldots, \underline{w}_P')'$ and the matrix $\mathbf{Y}(\delta) = (\mathbf{Y}_i(\delta)', \ldots, \mathbf{Y}_P(\delta)')'$, the complete multichannel model reads

$$\underline{s} = \mathbf{Y}(\delta) \cdot \underline{\alpha} + \underline{w}. \quad (9)$$

This relationship is exploited in the following to efficiently solve the pressure reconstruction problem and obtain a statistical test for misfire detection.

4. MULTICHANNEL PRESSURE RECONSTRUCTION AND MISFIRE DETECTION

The stochastic properties of the joint noise vector $\underline{w}$ suggest to use the maximum likelihood criterion [8] to estimate α and δ. Since $\underline{w}$ is jointly gaussian with block-diagonal covariance matrix $\mathbf{Q} =$

$\mathrm{E}\,\underline{w}\underline{w}' = \operatorname{diag}\{\mathbf{Q}_1, \ldots, \mathbf{Q}_P\}$, the log-likelihood function takes the form

$$L(\underline{\vartheta}) = c_1 - \frac{N_l}{2}\sum_{i=1}^{P} \ln \sigma_i^2 - \frac{1}{2}(\underline{s} - \mathbf{Y}(\delta)\cdot\underline{\alpha})'\mathbf{Q}^{-1}(\underline{s} - \mathbf{Y}(\delta)\cdot\underline{\alpha}), \tag{10}$$

where c_1 describes the constant terms.

The maximization of (10) must be carried out with numerical methods. For a fixed position parameter δ, this corresponds to solve a weighted least squares problem with a weighting matrix that is unknown but for its diagonal structure. Under weak assumptions, a two-step estimation based on iterating

$$\hat{\underline{\alpha}}(\underline{\sigma}^2, \delta) = \big(\mathbf{Y}(\delta)'\mathbf{Q}^{-1}\mathbf{Y}(\delta)\big)^{-1}\mathbf{Y}(\delta)'\mathbf{Q}^{-1}\underline{s} \tag{11}$$

$$\hat{\sigma}_m^2(\underline{\alpha}, \delta) = N_l^{-1}\big\|\underline{s} - \mathbf{Y}(\delta)\cdot\underline{\alpha}\big\| \tag{12}$$

behaves asymptotically for $N_l \to \infty$ like the weighted least squares estimator with known $\mathbf{Q}$ [9]. Once the estimates $\hat{\underline{\alpha}}^*$ and $\hat{\underline{\sigma}}^{2*} = (\hat{\sigma}_1^{2*}, \ldots, \hat{\sigma}_P^{2*})'$ have been obtained, the likelihood is calculated as

$$L(\hat{\underline{\alpha}}^*, \hat{\underline{\sigma}}^{2*}, \delta) = c_2 - \frac{N}{2}\sum_{i=1}^{P} \ln \hat{\sigma}_i^{2*} \tag{13}$$

and is used as fitting criterion in the search for $\hat{\delta}^*$.

Finally, the best parameter vector $\hat{\underline{\vartheta}}^*$ yields the reconstructed pressure shape for the l-th combustion as

$$\hat{\underline{x}}_l = \underline{x}(\hat{\underline{\vartheta}}^*) = \mathbf{X}(\hat{\delta}^*)\cdot\hat{\underline{\alpha}}^* \tag{14}$$

Notice that each of the combustions contained in the l-th data window also provides an estimate for the noise power $\hat{\sigma}_i^{2*}$. Similarly to the single channel case, their combination yields an estimate of the overall noise power of the different channels. Prior estimates, averaged over several data windows, can be used to initialize the two-step iterative method (11).

As proposed in [4, 5] for the single channel case, the reconstructed pressure can be used as misfire indicator. Since the trace resulting from a faulty combustion corresponds to the compression of a gas in a closed volume, the amplitudes α_2 and α_3 in (4) should be very small compared to the amplitude of the compression curve $u(\cdot)$. Specifically, the hypothesis *'misfire'* $\mathcal{H}_0$ should be tested against the alternative *'normal combustion'* $\mathcal{H}_1$, defined as

$$\mathcal{H}_0 := \{\alpha_1 \neq 0, \alpha_2 = 0, \alpha_3 = 0\}, \tag{15}$$

$$\mathcal{H}_1 := \{\alpha_1 \neq 0, \alpha_2 \neq 0, \alpha_3 \neq 0\}. \tag{16}$$

However, the lack of orthogonality between the curves of (4) makes more convenient to evaluate if the pressure signal contains components orthogonal to the compression curve. The hypotheses (15) and (16) will be reinterpreted accordingly in the following.

Actually, just the estimated position parameter $\hat{\delta}^*$ is used in the misfire test, while the amplitudes are recalculated. To approximate the sound components $\underline{s}_i$ (6), the EM algorithm combines a fraction of the estimated noise signal plus the reconstructed sound signature using therefore the parameters of the prior iteration. But this way, EM implicitly injects into the data the contribution we want to detect. Therefore, for the purpose of misfire detection, it is more convenient to reestimate $\underline{s}$ by subtracting all the sound signatures but the l-th one from the measured multichannel signal [4].

Formally, the signal model still corresponds to (6), but the noise power σ_i^2 now corresponds to the overall noise power for the i-th channel. Additionally, the σ_i^2 are assumed to be known, since they can be estimated by averaging over past combustions. More exactly, it is sufficient to know them up to a scaling factor, $\mathbf{K} = c\cdot\mathbf{Q}$, because only the ratio between them is relevant.

Let $\mathbf{P}_{\mathbf{A}}^{\mathbf{B}} = \mathbf{A}(\mathbf{A}'\mathbf{B}^{-1}\mathbf{A})^{\#}\mathbf{A}'\mathbf{B}^{-1}$ and $\mathbf{P}_{\mathbf{A}}^{\mathbf{B}\perp} = \mathbf{I} - \mathbf{P}_{\mathbf{A}}^{\mathbf{B}}$ be the projection and orthogonal projection matrices onto the column space of $\mathbf{A}$ with norm $\mathbf{B}^{-1}$, where $(\cdot)^{\#}$ denotes a generalized inverse and $\mathbf{I}$ the identity matrix. Using standard results from least squares theory for normally distributed errors and signal detection theory, it can be shown that

$$\mathcal{T} = \frac{P\cdot N_l - 3}{2}\,\frac{\underline{s}'\mathbf{Q}^{-1}\big(\mathbf{P}_{\mathbf{Y}(\hat{\delta})}^{\mathbf{Q}} - \mathbf{P}_{\tilde{\underline{u}}}^{\mathbf{Q}}\big)\underline{s}}{\underline{s}'\mathbf{Q}^{-1}\mathbf{P}_{\mathbf{Y}(\hat{\delta})}^{\mathbf{Q}\perp}\underline{s}} \tag{17}$$

is under the hypothesis $\mathcal{H}_0$ and the true δ $\mathcal{F}$-distributed with 2 and $P\cdot N_l - 3$ degrees of freedom, which also holds approximately for the current estimate $\hat{\delta}^*$. The numerator of (17) contains the energy of the sound signal associated to the complete pressure trace minus the part corresponding to $\tilde{\underline{u}}$, which yields the energy fraction orthogonal to the compression curve.

The test function (17) decides in favor of *'misfire'* when $\mathcal{T} \leq \mathcal{F}_{2,P\cdot N_l-3,\beta}$ holds, where the threshold represents the value that a $\mathcal{F}_{2,P\cdot N_l-3}$-distributed random variable surpasses with probability β. The probability of a correct misfire detection under the hypothesis is then $1-\beta$.

Notice that the interpretation of the test is inverse to the traditional approach. Commonly, the detector yields a certain signal detection probability for a previously set false alarm rate β. In our case, the objective is to detect the occurrence of misfire, i.e. the *absence* of signal, which happens with probability $1-\beta$ under the conditions stated before.

The possibility to set the theoretical misfire detection probability a priori is an useful feature from the application viewpoint, since this is the principal performance indicator specified in the environmental regulations. The dependance of the threshold on the combustion sample number N_l is also convenient because it can be adapted automatically to different engine speeds and sampling rates.

5. EXPERIMENTAL RESULTS

Although the quality of the reconstructed pressure is linked with the performance of the multichannel misfire detector, only the latter shall be evaluated with real measurement data collected from a four cylinder, 1.8 l, turbo charged, spark ignition test bed engine. All cylinders were equipped with a spark plug with integrated pressure sensor. Four acceleration sensors were mounted on the intake side of the engine approximately 10 mm below the cylinder head, each one close to the axis of one of the cylinders. Additionally, the crank angle was measured via a crankshaft sensor. After appropriate filtering, all the signals where downsampled to 2.5 kHz.

As detailed in [3], for each operating point a training data set was processed to identify the transfer functions $A(\cdot)$ and $H_k(\cdot)$ of the signal model (1), and also to obtain the three curves of the parametric pressure model (4). An independent data set at the same operating conditions was used to evaluate the misfire detector.

In [4] and [5] it was shown that with the theoretical threshold only a reduced number of misfires could be detected correctly. This can be attributed to the mismatch between the measured structure-borne sound and the signal model (1), and also to the

Sensor 1

Speed \ Load	High	Medium	Low
1000	–	100	100
2000	100	100 / 57 / 43	21 / 14 / 7
3000	100	100 / 93 / 86	43 / 7 / 0
4000	100	100 / 93 / 86	21 / 7 / 7
5000	100 / 100 / 92	69 / 38 / 31	21 / 14 / 14
6000	71 / 71 / 36	23 / 8 / 8	–

Sensor 3

Speed \ Load	High	Medium	Low
1000	–	100	100
2000	100	100 / 100 / 93	0 / 0 / 0
3000	100	100	57 / 29 / 29
4000	100	100	7 / 0 / 0
5000	100	77 / 77 / 77	71 / 50 / 21
6000	100 / 93 / 93	46 / 15 / 8	–

Sensor 1 and 3 (multichannel)

Speed \ Load	High	Medium	Low
1000	–	100	100
2000	100	100	29 / 21 / 14
3000	100	100	86 / 57 / 57
4000	100	100	36 / 29 / 29
5000	100	77 / 77 / 77	79 / 43 / 29
6000	100	62 / 46 / 46	–

Table 1. Cumulative experimental results for 1000 combustions with 13 to 14 misfires, for the accelerometers located at cylinder 1 and 3. For each operating point, the misfire detection probability (in %) for an empirical misfire false alarm of (5%/1%/0.5%) is shown. Not evaluated operating conditions are marked with a '-'.

limitations of the pressure parametrization (4). However, especially for high load and/or low speed, the test function discriminated very well between both types of combustions, and a slight adjustment of the threshold was enough to obtain useful detection rates.

Table 1 summarizes the results obtained with the accelerometers located at cylinders 1 and 3, both on their own and combined in a two-channel signal. Three load conditions (high, medium and low) and six different engine speeds (from 1000 to 6000 rpm) were considered. A total of 13 to 14 misfires at different cylinders were present among the 1000 combustions contained in each data set. Since the reduced number of misfires does not allow to set an arbitrary detection threshold a priori, the triplets in the table show the misfire detection probability for an empirical threshold that mistakes normal combustions with probability 5%, 1% and 0.5%, respectively.

As it is common to all existing misfire identification procedures, the combination of low load and high speed define the most critical operating points. For weak combustions, both the overall energy of the signal and the pressure rise of a successfull combustion decrease, thus affecting the accuracy of the pressure reconstruction. On the other hand, the number of combustions that contribute to the sound in a given data window increases with the engine speed, which makes the signal decomposition more difficult.

The results illustrate the superior performance of the multichannel detector when compared with the single channel counterparts. With respect to the latter, it is observed that, for both sensors, the figures at the speeds of 2000 and 4000 rpm and low load are comparatively low, but the reason for this behavior is not known yet. However, though the improvement yielded by the multichannel approach is most significant in the lower right corner of the table, still better detection ratios are needed for an implementation in commercial engines. A straightforward solution is to combine the signals from more accelerometers at the cost of an increased computational load. Moreover, it should be mentioned that the sampling rate employed in the simulations is much lower than the one conventionally used in the literature; in the present conditions, at 6000 rpm a sampling period corresponds to 14.4° crank angle, while usually the pressure and sound signals are sampled with a resolution of 1° for analysis.

6. CONCLUSIONS

The paper exploits the signal decomposition achieved by the EM algorithm to reconstruct in-cylinder pressure traces from multichannel sound signals. Under this framework, we devise a conceptually simple misfire test that is based on the shape of the reconstructed pressure and that is shown to outperform the single channel solutions. Though the improved misfire detection probabilities still does not satisfy existing regulations, the combination of more accelerometers and higher sampling rates for high speed operating points leaves room for improvement.

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