

Capturing Cyclic Variability in SI Engine with Group Independent Component Analysis

Katarzyna Danuta Bizon
Cracow University of Technology

Simone Lombardi and Gaetano Continillo
Universita del Sannio

Paolo Sementa and Bianca Maria Vaglieco
Istituto Motori CNR

ABSTRACT

Data decomposition techniques have become a standard approach for the analysis of 2D imaging data originating from optically accessible internal combustion engines. In particular, the method of Proper Orthogonal Decomposition (POD) has proven to be a valuable tool for the evaluation of cycle-to-cycle variability based on luminous combustion imaging and particle image velocimetry (PIV) measurements. POD basically permits to characterize the dominant structures of the process under consideration. Recently, an alternative procedure based on Independent Component Analysis (ICA) has been introduced in the engine field. Unlike POD, the method of ICA identifies the patterns corresponding to physical processes that are statistically *independent*. In this work, a Group-ICA approach is applied to 2D cycle-resolved images of the luminosity emitted by the combustion process. The analysis is meant to characterize cyclic variability of a port fuel injection spark ignition (PFI SI) engine. For example, any flame front ignited independently by a hot spot is expected to behave independently from the other observed flames. In the Group-ICA approach, image sequences collected synchronically over a number of cycles are grouped together and then analyzed to identify common independent components. These should correspond to the independent phenomena underlying the combustion process at the group level. By this way, a projection is implicitly defined that permits the reconstruction of each member of the group (cycle) through the independent components and their coefficients. The successive analysis of the associated time courses (coefficients), specific for each cycle, permits to capture and discuss differences among cycles.

CITATION: Bizon, K., Lombardi, S., Continillo, G., Sementa, P. et al., "Capturing Cyclic Variability in SI Engine with Group Independent Component Analysis," *SAE Int. J. Engines* 8(5):2015, doi:10.4271/2015-24-2415.

INTRODUCTION

Cyclic variability phenomena in spark ignition engines (SI) are recognized to have strong negative influence on engine performance, and can also lead to knocking or misfire. Prediction and control of cyclic variability is an issue of prime necessity for automotive manufacturers. Cycle-to-cycle variation occurrence is caused by a number of strongly coupled factors/phenomena, i.e. variation of spark discharge characteristics, in-cylinder mixture and its distribution near the spark plug, turbulence intensity and overall in-cylinder flow pattern, just to mention a few. The extent of the variability can be quantified by the evaluation of thermodynamic quantities, e.g. in-cylinder pressure [1]. Yet, the analysis of the time series of a single scalar variable does not enable to fully understand the role of different factors. Much more information about variations in flame kernel growth and its propagation, or possible abnormal combustion, can be obtained through cycle-resolved visualization of the combustion process both in terms of velocity maps and combustion light emission images.

To take full advantage of the information contained in spatiotemporal data, and to extract information on the cyclic variability from the distributed data, the measurements performed via modern high speed and high resolution techniques [2] have to be accompanied by appropriate mathematical and analytical tools. During the last decade, the method of Proper Orthogonal Decomposition [3] has become a standard tool for the analysis of engine data, giving an important contribution to the knowledge of in-cylinder processes. In particular, Roudnitzky et. al [4] proposed a filtering approach for evaluation of cycle-to-cycle variations, based on POD and statistical moments, with the application to the analysis of cold flow PIV measurements in SI engines. An alternative approach was proposed in [5-6], where the method was associated with luminous combustion imaging. This resulted in the extraction of information on cyclic variation phenomena, for the first time, from non-intrusive measurements of light emission during the combustion process. A more recent work [7] reports on POD-based identification and quantification of cyclic

variations in the intake air motion and spray structure in the cylinder of a SI direct injection optical engine. The method was later used [8] to assess cycle-to-cycle variations of early flame propagation.

Essentially, POD identifies underlying structures that are orthogonal to each other. Without doubts, POD is a powerful tool for the characterization of a given data in terms of dominant/coherent and incoherent structures. Yet, there is no reason to believe that orthogonal structures be necessarily related to different, independent physical processes. An alternative decomposition, based on physically realistic assumptions, is the Independent Component Analysis (ICA) [9]. ICA reveals hidden factors that underlie sets of measurements, by determining components on the basis of their mutual statistical independence. Unlike POD, which basically permits to characterize the *dominant* structures of the examined process, ICA identifies and separates patterns corresponding to *independent* physical processes. In the engine context, ICA has been used to identify the source signals related to independent mechanical events from acoustic measurements [10] and vibration signals [11]. Recently [12] the method was employed for the analysis of the dynamics of a single cycle and of cyclic variability in a Diesel engine, demonstrating superiority of ICA over POD in terms of information retrieved. Later on, an attempt of analysis of the dynamics of flame images collected from a SI optical engine was reported in [13]. The analysis recovers and separates different combustion phases which result to be grouped according to their temporal succession: ignition and premixed flame propagation, intermediate combustion phase and the final flame burn out.

In this work, a Group-ICA approach is applied to 2D cycle-resolved, line-of-sight integrated, luminosity images, collected from a port fuel injection spark ignition (PFI SI) engine. In the Group-ICA approach, image sequences collected synchronically over a number of cycles are grouped together and, then, common independent components are determined. The successive analysis of the associated temporal coefficients, specific for each cycle, together with engine parameters, permits to quantify cyclic variability.

EXPERIMENTAL SETUP

The experiments employ an optically accessible single cylinder spark ignition (SI) engine for 2D measurements of the combustion-related luminosity (Figure 1). The engine, equipped with the cylinder head of a small port fuel injection (PFI) SI engine, has four valves and a centrally located spark plug. A quartz pressure transducer is flush-installed in the region between intake and exhaust valves. The fuel is fed via a commercial 3-holes injector, at 3.5 bar injection pressure. The elongated engine piston is modified and made transparent by means of a sapphire window. Table 1 reports basic engine specifications. Further details of the experimental setup are in Ref. [14].

All of the tests are performed at 2000 rpm with spark timing at -34° CA. The intake air pressure and temperature are 1600 mbar and 298 K, respectively. The engine is fuelled with commercial gasoline at stoichiometric equivalence ratio.

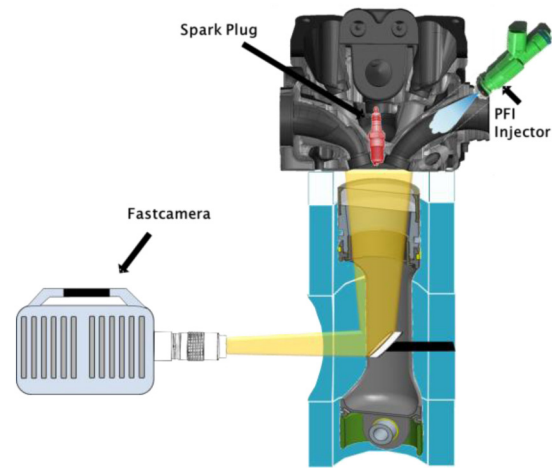


Figure 1. Experimental setup.

The luminosity emitted by the combustion process is reflected by means of 45° inclined UV-visible mirror located at the bottom of the engine, and conveyed towards the image acquisition setup made of a 78 mm focal length, f/3.8 UV Nikon objective, followed by a CMOS 16-bit high speed camera with spatial resolution of 1024×1024 pixels. The image collection process clips a region of 896×496 pixels, allowing for a spatial resolution of around 0.11 mm/pixel, and employs a frame rate of 30000 fps which, for the engine operating at 2000 rpm, correspond to 0.4° CA increments from frame to frame. The exposure time is 30 μ s.

Table 1. PFI SI engine specifications.

Displacement	250 cm ³
Bore	72 mm
Stroke	60 mm
Connecting rod	130 mm
Compression ratio	10.5:1

THEORETICAL BACKGROUND

Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is a method that permits to discover hidden factors, i.e. source signals or features, from a set of observed data. The search is conducted via an optimization algorithm ensuring that the discriminated sources are maximally independent. A basic ICA mixing model assumes that $\mathbf{s}(t) = [s_1, s_2, \dots, s_N]^T$ (the source signals) are not observable, mutually independent, and combined with an unknown linear superposition (or "mixing") process. Considering the vector of the observations $\mathbf{x}(t) = [x_1, x_2, \dots, x_N]^T$, also called mixtures, the ICA model, in vector-matrix notation, can be written as:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \quad (1)$$

where $\mathbf{A}$ is an unknown mixing matrix. For simplicity, the assumption is made that the observations are in the same number of the sources, i.e. $M = N$. The goal of ICA is then to find the estimate $\mathbf{W}$ of the unmixing matrix $\mathbf{A}^{-1}$, such that $\mathbf{y}$, given by:

$$\mathbf{y} = \mathbf{W}\mathbf{x} \quad (2)$$

is a good estimate of the original source signals, i.e. *independent components*, $\mathbf{s}$. Note that each of the components may well be representative of a nonlinear process, such as a flame; linearity is only assumed for the combination of the independent sources.

A variety of algorithms were developed to solve the ICA problem. The most popular approaches are based on minimization of the mutual information between pairs of source signal estimates, or maximization of non-Gaussianity of the source signals estimates. In this study, a FastICA (a fast fixed-point algorithm [9]) is used. The algorithm, by means of a gradient method, maximizes non-Gaussianity, estimated by the absolute value of the kurtosis as a measure of statistical independence. Prior to executing ICA, the sample mean is subtracted from the observed data $\mathbf{x}$, namely:

$$\mathbf{x} \leftarrow \mathbf{x} - E\{\mathbf{x}\} \quad (3)$$

where $E\{\cdot\}$ is the ensemble average. Then, the output of the centering transformation defined by Eq. (3) is *whitened*: the whitening procedure consists of a data transformation such that the components of the resulting vector are uncorrelated and have unit variance, i.e.:

$$\mathbf{x} \leftarrow \mathbf{\Lambda}^{-1/2} \boldsymbol{\Phi}^T \mathbf{x} \quad (4)$$

where $\boldsymbol{\Phi}$ is an $M \times M$ matrix whose columns are the eigenvectors of the data covariance matrix, defined as:

$$\mathbf{C} = E\{\mathbf{x}\mathbf{x}^T\} \quad (5)$$

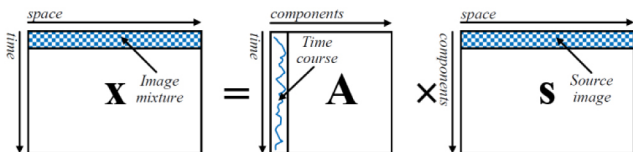


Figure 2. Vector-matrix representation of mixing process for images.

while $\boldsymbol{\Lambda}$ is the diagonal matrix of the eigenvalues of $\mathbf{C}$; $\boldsymbol{\Phi}$ and $\mathbf{\Lambda}$ are computed by solving the problem:

$$\boldsymbol{\Lambda} \boldsymbol{\Phi} = \mathbf{C} \boldsymbol{\Phi} \quad (6)$$

In some cases, $M \geq N$, that is the number of underlying signals N to be determined is smaller than the number M of mixtures available, making $\mathbf{A}$ a non-square matrix, whose inverse $\mathbf{W}$ cannot be

determined. The dimension of the observed data $\mathbf{x}$ can be thus reduced by means of discrete Proper Orthogonal Decomposition (POD) [15]. This is done during the whitening given by Eq. (4) and employing in the transformation the submatrices consisting of the first N rows and columns of $\mathbf{\Lambda}$ and the first N columns of $\boldsymbol{\Phi}$. When dealing with a sequence of images [16], as in this study, the notation remains basically the same. Each image is viewed as a mixture of some underlying spatial features (source images). To determine these mutually independent spatial structures, each image, supposedly made of $X \times Y$ pixels, is represented as a vector by concatenating its rows, and treated as a mixture x_i of length $L = X \times Y$. Thus, the (temporal) sequence of M images constitutes the observation vector $\mathbf{x}$ (Figure 2). Using ICA, the set of observed image mixtures is then decomposed into a set of independent source images $\mathbf{s}$ and a corresponding set of unconstrained temporal courses $\mathbf{A}$. Each time course (column of matrix $\mathbf{A}$) quantifies the contribution of the associated independent source to the observed temporal sequence of image mixtures.

Group-ICA Approach

For a given group of image sequences illustrating a repeatable, to some extent, physical process, it would be natural, in the ideal case, to assume that the sequences are combinations of identical spatial structures. Then, the variations observed among the sequences are quantified by the associated time courses, e.g. by their amplitude. In general, various ICA approaches have been proposed in the literature [17] for the analysis of underlying structures and sequence variability at the group level. The simplest approach consists of performing ICA separately for each element of the group (sequence of images) and then attempt to combine the output into groups, e.g. using the spatial correlation of the components. The disadvantage of this procedure is the fact that the components are not necessarily unmixed in the same way for each group. Under the assumption of the spatial stationarity of the underlying processes, i.e. occurrence of spatial structures at the same position and with the same shape, it is more appropriate to determine the common spatial components.

To this aim, all images are first represented as vectors to create, for each image sequence, an observation array, x_j , $j=1, \dots, K$, where K is a number of sequences in a group. Then, a temporal concatenation of the arrays is performed to create a unique array of mixtures, $\mathbf{x}$ (Figure 3). This approach allows to determine unique time courses, $\mathbf{A}^j$, $j=1, \dots, K$, for each member (sequence of images) of the group by assuming common group maps, $\mathbf{s}_{com}$.

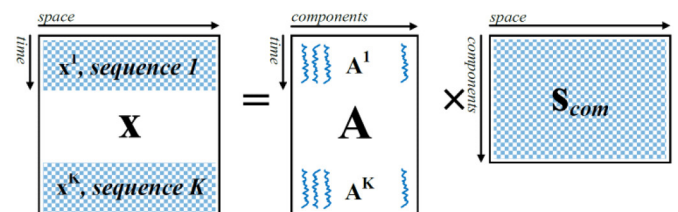


Figure 3. Vector-matrix representation of mixing process for images.