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Independent component analysis of cycle resolved combustion images from a spark ignition optical engine

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ABSTRACT

This paper reports on the application of independent component analysis (ICA) to 2D cycle-resolved images of the luminous combustion, collected in a port fuel injection spark ignition optically accessible engine. The method of ICA is employed for the identification of the independent spatial components, which along with the corresponding time dependent coefficients, represent the spatiotemporal evolution of the luminous combustion during a single cycle and over a number of cycles. ICA is applied on the data preprocessed by proper orthogonal decomposition (POD). POD-filtered ICA permits to determine only few dominant and relatively easy interpretable independent components. Successively, and for comparison, ICA is applied to the non-truncated data. It is demonstrated that ICA applied to single cycle permits to extract independent structures, clearly separated in time. The time dependent coefficients correlate well with the integral flame luminosity, and characterize time evolution of the combustion pattern in the chamber. The analysis over several cycles shows that independent components carry information about the dominant morphology of the cyclic variations. The low correlation of the corresponding (in terms of time succession) components for successive cycles is in agreement with the high spatial variability of the combustion process in spark ignition engines, mainly due to the combustion of fuel pockets created in the combustion chamber by the injection process. A different approach is then proposed, enabling separation of sources corresponding to objects moving in the field of view. Each whole sequence of 2D images (video) is considered as a single observed mixture of independent signals. Both linear and nonlinear mixing models are considered, and artificial examples are used to illustrate features and limitations of linear ICA when applied to nonlinear mixing. The procedure is successfully applied to a video reporting the motion of a luminous flame over a portion of the cylinder head. ICA separates the moving source from the background, with a mechanism explained by a nonlinear mixing model.

1. Introduction

The progress of high speed imaging of reactive flows opened up a wealth of new investigation activities of the mixing process, flame ignition and extinction, particularly in internal combustion (IC) engines, allowing progress towards cleaner and more efficient combustion, and contributing to the development of predictive models [1,2]. The high camera frame rates, the high spatial resolutions, and the huge storage and elaboration capabilities available nowadays, permit to diagnose spatially distributed in-cylinder processes characterized by very fine spatial structure and very short time scales. However, to fully take advantage of the abundance of information contained in spatiotemporal data, the continuing improvement in the imaging and data storage technologies has to be accompanied by the development of advanced analytical techniques.

In many works this issue was addressed by means of proper orthogonal decomposition (POD) [3], which, restricted to a finite-dimensional case, is equivalent to principal component analysis (PCA) [4]. The capabilities of POD – both as an order reduction method and as a tool for feature extraction – resulted in growing popularity of this technique in many fields: among others, fluid mechanics [5-7], chemical engineering [8,9] and combustion [10,11]. Over the last decades, it has also proven to be a useful tool for the analysis of engine data, giving a great contribution to the knowledge of in-cylinder processes. Among other applications, it was used for the analysis of the flow structure from cold-flow measurement data, computational fluid dynamics and particle image velocimetry (PIV)

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[12]. In Ref. [13] the cyclic variability of velocity fields in a spark ignition (SI) engine was characterized in terms of mean, coherent and incoherent structures employing POD-based filtering approach. An alternative approach, aimed at cycle-to-cycle variation in both SI and Diesel optical engines, and based on the statistical analysis of the POD coefficients, was proposed in [14,15], where, particularly, the method was associated with luminous combustion imaging, extracting for the first time information on cyclic variation phenomena from non-intrusive measurements of light emission during the combustion process. Ref. [15], by means of a synthetic example, discusses in detail how POD modes characterize highly variable engine combustion detectable in the morphology of combustion images even when traditional engine parameters do not change over cycles. Statistical analysis of the POD coefficients was then proposed in [16] for the evaluation of well-burning and misfiring cycles in SI engine. A more recent work [17] reports on the POD-based identification and quantification of cyclic variations in the intake air motion and spray structure in the cylinder of SI direct injection optical engine, and later used [18] to access the cycle-to-cycle variations of early flame propagation.

POD decomposes a given ensemble of spatiotemporal data into a set of orthogonal modes, which constitute the optimal, in the sense of the L^2 norm, basis [3]. This formal optimality makes POD the preferred basis when it comes to model reduction or data reduction, as it provides the most efficient way of capturing the dominant components of infinite- or high-dimensional processes with only finitely many, and often surprisingly few, modes. However, POD does not always guarantee that the maximum amount of the information is extracted: in fact, there is no reason to believe that underlying factors are orthogonal. In other words, while the purpose of the method such as POD is to find a faithful representation of the data, in the sense of reconstruction error, some more sophisticated methods try to find a representation more meaningful from the physical point of view. In particular, an alternative to be considered in IC engine applications is the independent component analysis (ICA) [19], which is increasingly utilized in a wide range of signal processing and imaging applications. ICA reveals hidden factors that underlie sets of measurements, by determining components on the basis of their mutual statistical independence. The first applications of ICA dealt with the so-called *cocktail party problem* [20], in which ICA was employed to determine individual speech waveforms from their mixtures. Since its introduction in the early 1980s, ICA has found many successful applications: from speech processing [21], brain imaging [22], to stock market analysis [23]. Particularly in the engine context, ICA has been used to identify the source signals related to independent mechanical events from acoustic measurements [24] and vibration signals [25]. Another example of ICA application in combustion can be found in [26], where the method was applied to identify the fuel type in power plants from flame oscillation signals.

Recently [27] ICA was employed for the analysis of the dynamics of a single cycle and cyclic variability of Diesel engine combustion, demonstrating superiority of ICA over POD in terms of information. It was reported that, in the analysis of the single cycle, the components extracted are clearly related to different combustion modes, whereas the analysis over cycles, individually at each crank angle position, separates the mean luminosity field from the random structures related to cyclic variations. In the second case, the separation is not very effective at the crank angle positions at which the cyclic variability is higher, i.e. at the end of combustion when the flames move randomly near the bowl wall. This finding indicates that the employed approach will be even less effective for the characterization of the combustion process in the gasoline engine, which is characterized by much stronger cyclic variation and substantially different physics with respect to combustion in Diesel engines. Some attempts to the analysis of flame images collected from an SI optical engine were reported in [28], however limited to the analysis of the dynamics of a single cycle. The analysis recovers and separates different combustion phases with the results grouped according to their temporal succession. An alternative method for the analysis, using grouping of image successions (cycles), is presented in [29].

Table 1
Specifications of the single cylinder SI engine.

Displacement (cm^3)	250
Bore (mm)	72
Stroke (mm)	60
Connecting road (mm)	130
Compression ratio	10.5:1

The present work is a continuation of these studies [27-29]. First, applications of two ICA-based methods are presented and compared. Spatial ICA (sICA) [30], both in the POD-filtered variant and in its full version, essentially identifies independent spatial structures and their corresponding time-dependent coefficients. A synthetic example, mimicking luminosity patterns of spark ignition combustion, is constructed and discussed to illustrate the capability of Spatial ICA to identify independent phenomena from mixtures of time-dependent two-dimensional images. Then, sICA is applied to cycle-resolved images from a port fuel injection spark ignition (PFI SI) engine: ICA, preceded by a POD-based data reduction phase (POD-filtered ICA), is used to determine a relatively low number of easily interpretable components. The determined components and their coefficients are utilized to analyze flame evolution and cyclic variability. ICA is then applied to the whole data set with no data reduction (Full ICA), and a large number of independent components are determined which are successively ordered, according to a proposed criterion, and compared with the corresponding components obtained from the low dimensional data.

We must recognize, though, that typical experimental imaging data are 2D space projections of time dependent phenomena, and that independence may be found both in space (e.g. separate independent flames in the field of view) and time (e.g. independent flames igniting at different times). A better way to deal with time evolutionary phenomena would perhaps be to use spatiotemporal ICA [30], a method that may eliminate any bias towards either dimension (space or time) in terms of search for independence. In essence, stICA consists of a multiobjective optimization in which a measure of space independence and a measure of time independence are both maximized for the components to be sought. Stone et al. [30] implemented a weight method, in which the two measures are weighted and combined to provide a single objective function. In stICA, however, space and time are still treated separately, whereas independent phenomena in the combustion chamber may well have a complex spatiotemporal structure. To deal with this, in the development of this work we apply ICA to our spatiotemporal data set, rearranged in such a way that each individual observation (mixture) incorporates the whole time-dependent phenomenon. In practice, a whole sequence of snapshots (the "video") constitutes the single observation, collected in a single array as a sequence of intensity values scanned over pixels and time instant, rather than, as with sICA, individual separately time-sampled snapshots. The method is illustrated on a synthetic example.

Finally, nonlinear mixing issues are treated, again with the help of a synthetic example. The performance of ICA and its limitations – due to the linear mixing operator assumption – are discussed, both on a synthetic example and on a sequence of combustion images.

2. Experimental setup

The optically accessible single cylinder spark ignition (SI) engine (details in Table 1) is equipped with the cylinder head of a small port fuel injection (PFI) gasoline engine, having four valves and a centrally located spark plug. Figure 1 reports a sketch of the optical apparatus