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Data reduction method for droplet deformation experiments based on High Order Singular Value Decomposition

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ABSTRACT

The work presented in this article describes a data reduction method for droplet deformation experiments carried out in a rotating arm facility. The reduction method is based on the technique known as High Order Singular Value Decomposition (HOSVD). The idea is to find out whether, in this context, HOSVD allows for sufficient generalization of the results in a way that the outcome of new cases can be reasonably predicted with no need for further experiments. Droplets were generated and allowed to cross the path of an incoming airfoil attached to a rotating arm. A high speed camera was used to record droplet deformation as a function of time. The flow field was characterized via Particle Image Velocimetry. Airfoil velocity was varied between 50 m/s and 90 m/s. Droplet radius was in the range from 200 μm to 600 μm. Three different self-similar airfoils were used in the experiments with leading edge radii varying from 0.030 m to 0.103 m. The generated droplet deformation data was organized in the shape of a tensor having four dimensions: airfoil velocity, airfoil leading edge radius, droplet size, and time along droplet trajectory. The results obtained show that, in this problem, HOSVD can be reasonably used to densify the original experimental data tensor with acceptable accuracy. Thereby, allowing for the generation of reliable new information without having to perform additional experiments.

1. Introduction

Data reduction is an important issue whenever experimental testing is involved. Its objectives are manifold; among others: to gather a better knowledge of the underlying physics, to generate scaling and/or design laws, and to further generalize results so as to uncover additional information without the need to perform additional experiments. Broadly speaking, data reduction methods can be classified into two main categories: those that rely on the model equations of the problem and those that do not. It is certainly much better to have a model, and methods that use this approach are able to perform the data reduction in the light of a deeper physical insight. However, this is not always possible because of a number of reasons; among them physical model uncertainties, complex geometries and/or boundary conditions, and so on. Then, experimental researchers have developed a wide variety of methods that search for internal self-consistency and coherence of the collected data without reference to a specific physical model. Three examples, among many others, that involve data reduction in the context of the fluid equations of motion are those of Wang et al. [1], Kirk [2], and Vukoslavcević [3]. In the first article, Wang et al. [1] developed a data reduction method to predict the performance of a certain type of heat exchangers. The theoretical model in which their reduction method was based was zero-dimensional and did not involve local values of the variables. In the second article, Kirk [2] developed a thermo-fluid based data reduction scheme for hypervelocity experiments in a high speed wind tunnel at NASA. The method concentrated on modeling the error induced by different factors and involved the resolution of a computational fluid dynamics scheme. In the third article, Vukoslavcević [3] developed a data reduction method for a hot wire probe. The method involved the realization of a virtual experiment and the computation of local velocities and gradients. Regarding methods that do not directly involve physical model equations, Benay [4] has used a Levenberg algorithm for data reduction applied to a seven holes probe. One of the main objectives of the study was to reduce the size of the required data set needed for calibration purposes. Ni et al. [5] used a Hilbert-Huang transform to develop a simple, yet robust, data reduction method to determine hydraulic parameters in the Taipei basin. A Fourier transform (combined with a theoretical model) based data reduction method

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to evaluate local heat transfer coefficients has been proposed by Cossali [6]. A Wiener filtering technique for thermo-graphic data reduction of fin plate results aiming to estimate heat transfer coefficients has been proposed by Rainieri et al. [7]. Although it may not be formally called data reduction, it is worth mentioning in the context of this article the study presented by Druault et al. [8]. Specifically, the authors used a Proper Orthogonal Decomposition (POD) approach to interpolate in between consecutive PIV (Particle Image Velocimetry) time resolved frames. The fact that they were able to do so is linked to the property that POD modes have of efficiently and hierarchically storing dataset information patterns. Then, once these global modes were computed out of the finite set of PIV experimental frames, an algorithm was devised to fill in new information that was consistent with the POD global modes. In a context different from thermo-fluid-mechanics, Empirical Mode Decomposition (EMD) has been used by Rosas-Cholula et al. [9] for headset data analysis and reduction purposes. Related to inverse analysis, Hwang et al. [10] have used wind tunnel data in combination with a Kalman filter to achieve accurate identification of wind loads. A completely different approach to wind tunnel data reduction based on the use of a neural network has been proposed by English and Fricke [11]. Again, this may not be called data reduction on a strict sense, but the purpose was to generalize data so as to make accurate predictions of variables of interest. Aiming to generalization, Partridge and Keyhani [12] have published a generic data reduction method for interferometric data. Finally, although far apart from a thermo-fluid-mechanics area, it is interesting to quote the work of Nickerson and Sloan [13] that used a multivariate data reduction technique to generate both a reduced performance vector and a reduced set of decision variables in the context of a semiconductor production benchmarking study.

The objective of the present article is to describe a High Order Singular Value Decomposition (HOSVD) based data reduction method for the four dimensional data set obtained in a rotating arm facility regarding droplet deformation in the vicinity of an incoming airfoil. After this introduction, the experimental setup is described in the next section. Then, the HOSVD technique in view of this specific application is described and the results obtained are presented. Finally, conclusions are given with regard, among other things, to the issue of how to optimize data acquisition in future experimental campaigns in a rotating arm facility.

2. Description of experimental setup

An experimental campaign was carried out to obtain the time evolution of droplet deformation in a flow field generated by an incoming airfoil at INTA rotating arm facility in Spain near Madrid. This work was part of a much broader collaboration between INTA and NASA [14]. The rotating arm facility consists of a 5 kW vertical axis electric motor placed inside a support structure, and a rotating arm whose length is 2.2 m and that rotates at velocities up to 400 rpm. Three Styrofoam airfoils of the same geometry but different size, labeled as M1, M2 and M3, were attached to the end of the rotating arm, resulting in translational velocities up to 90 m/s. Five velocities were selected during the experiments: 50 m/s, 60 m/s, 70 m/s, 80 m/s and 90 m/s. The shape parameters for each airfoil model and the dimensionless airfoil's coordinates are specified in Tables 1 and 2 respectively. Also, some views of the airfoil are presented in Fig. 1. It could be observed that the airfoils are rather thick and blunt so as to reproduce the actual scale of the problem more accurately.

The flow field generated by these airfoils in the rotating arms facility was characterized using a TSI Particle Image Velocimetry (PIV) system which consisted of two pulsed Nd-Yag 190 mJ lasers to provide illumination, a Power View Plus 4MP camera to record the images with a resolution of 2048×2048 pixels, and different sets of camera lenses (AF-S VR Micro Nikkor 105 mm f/2.8 G IF-ED Nano Crystal Coat, AF Nikkor 80–200 mm f/2.8 D IF-ED, and Nikkor 50 mm f/1.4). The flow was seeded with olive oil droplets of 1 μm of diameter. The TSI Insight 3G software was used to operate the TSI Laser Pulse Synchronizer and synchronize image capturing and flow illumination, and to perform the subsequent analysis. Time between two consecutive laser pulses varied between 1.1 μs and 200 μs. For the fastest moving airfoil, a particle moves about 3 mm between two consecutive pulses. This is a distance much smaller than airfoil leading edge radius (which is the characteristic length of the problem). Additional details on the PIV measurement procedure to generate the required flow field are given in the work by Garcia-Magariño et al. [15]. A typical example of the measured average flow field in the vertical plane tangent to the path of the model is shown in Fig. 2 (top). The spatial flow field resolution in the test windows near the airfoil leading edge was of the order of 1 mm. It is also of interest, because of characterization purposes, to measure the flow velocity along the airfoil stagnation line. This is plotted as a function of the dimensionless distance to the model, see in Fig. 2 (bottom).

Then, a stream of water droplets whose radii was the range between 200 and 750 μm was allowed to fall in the path of the incoming airfoil as it is sketched in Fig. 3.

The water droplets were generated by a monosized TSI MDG-10 droplet generator. The operating principle of this droplet generator is based on the theory of Strutt and Rayleigh [16] who analyzed the instability of capillary jets back at the end of the nineteenth century. Because of axisymmetric disturbances, a laminar jet can break up into droplets, and Strutt and Rayleigh [16] gave the optimal wavelength of the fastest growing disturbance for an inviscid fluid (4.44 times the jet diameter). When a sinusoidal disturbance having the frequency corresponding to the optimal wavelength (the so-called Rayleigh frequency) is applied to the jet, a monosized stream of droplets is generated at this frequency rate. Mass flow conservation considerations (one single droplet is formed out of each liquid cylinder portion one wavelength long) allows for the calculation of the droplet diameter "d" of the monodisperse stream as a function of the jet volume flow rate "Q" and the applied vibra-

Table 1
Geometry parameters of the three airfoils: M1, M2, and M3.

Model	Chord (c)	Leading edge radius (R_c)	Thickness (T_c)
M1	0.690 m	0.103 m	0.276 m
M2	0.468 m	0.070 m	0.187 m
M3	0.199 m	0.030 m	0.080 m

Table 2
Dimensionless coordinates of the airfoils.

x/c	z/c	x/c	z/c
1.000	0.000	0.241	0.200
0.937	0.014	0.211	0.196
0.877	0.028	0.183	0.191
0.818	0.044	0.157	0.183
0.762	0.059	0.133	0.173
0.707	0.076	0.110	0.162
0.655	0.093	0.090	0.150
0.604	0.110	0.072	0.136
0.556	0.127	0.056	0.121
0.510	0.143	0.042	0.105
0.465	0.158	0.030	0.089
0.423	0.171	0.020	0.072
0.383	0.183	0.012	0.055
0.344	0.192	0.006	0.041
0.308	0.198	0.002	0.032
0.274	0.200	0.000	0.000