

# Dynamic mode decomposition for analyzing two-phase flow video data

E. M. Ramos<sup>1</sup>, G. M. Darze<sup>2</sup>, J. L. H. Faccini<sup>2</sup>,  
G. A. Giraldi<sup>1</sup>  
E-mail: [faccini@ien.gov.br](mailto:faccini@ien.gov.br)

<sup>1</sup>LNCC, <sup>2</sup>SETER-IEN

**Keywords:** dynamic mode decomposition, two-phase flow, video frames processing.

Dynamic mode decomposition (DMD) has been used for numerical and video data analysis in fluid flow, [1]. Despite of its advantages, we have noticed some issues in the DMD methodology: (a) Although the number  $N$  of snapshots used to compute the dynamic modes is a fundamental parameter, there is not a systematic procedure to set it; (b) The number  $N$  may vary along the simulation; (c) In the case of two-phase flow the investigation of the phase interface preservation in the dynamic modes has not been considered in previous works. In this paper, we address these issues using two-phase flow videos (slug and stratified) recorded as a case study. Firstly, we address the choice of  $N$  by using a methodology based on space-time correlation. Each video sequence segment obtained is further analyzed considering linearity properties and the norm of the residual vector. In this way, we can partition the flow sequence into  $M$  segments (Tab. 1(a)) which allow to accomplish issue (b). Next, we apply the traditional DMD as well as the sparsity-promoting DMD (SPDMD) and compare the results regarding to the phase interface preservation, as shown in Fig. 2 (a)-(b). So, we propose a segmentation approach to automatically extract the interface obtained by both DMD and SPDMD video reconstructions (Fig. 2 (b)-(d)) and compare them with the original data. The obtained result is used to compare the efficiency of both DMD strategies. Finally, we compare DMD and SPDMD results regarding to the phase interface preservation and conclude that the DMD technique is more efficient than SPDMD respect to this item, [2]. The video data is acquired through a test section that is shown in Fig. 1.

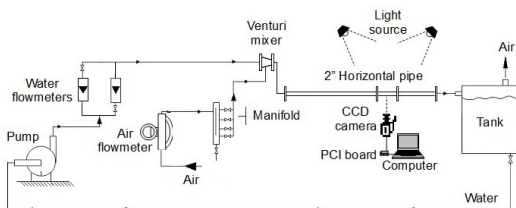


Fig. 1. Schematic of test section with the visualization systems.

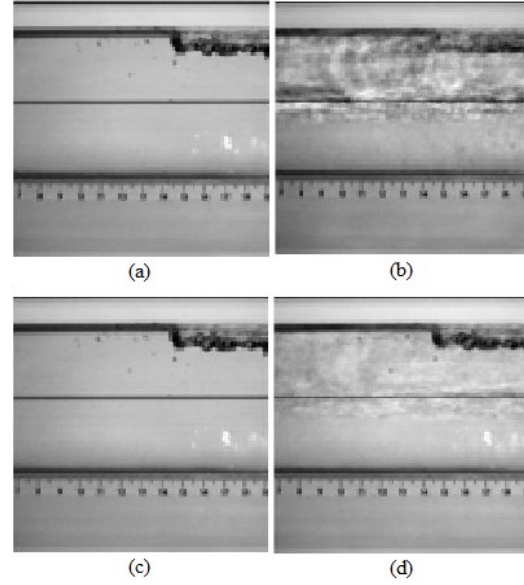


Fig. 2. (a) Reconstruction of frame number 6 using DMD. (b), (c), (d) Frame number 6 reconstructed using the SPDMD.

Table 1. (a) Intervals obtained for slug flow video with the pipeline: cross-correlation, total variation, differentiation operator, and thresholding. (b) Local errors and Global reconstruction errors.

Resolution	Intervals
100	38,98,181,249,303,374,452,500
200	38,102,181,249,303,374,451,502
300	38,102,181,249,303,374,451,502

(a)

Resolution	Local Errors	Global Errors
100	[ $6.6 \times 10^{-14}$ ; $2.7 \times 10^{-12}$ ]	[0.084; 0.308]
200	[ $1.8 \times 10^{-14}$ ; $5.7 \times 10^{-13}$ ]	[0.042; 0.15]
300	[ $1.5 \times 10^{-14}$ ; $5.1 \times 10^{-13}$ ]	[0.028; 0.103]

(b)

## References

- [1] JOVANOVIĆ, M. R.; SCHMID, P. J.; NICHOLS, J. W. Sparsity-promoting dynamic mode decomposition, *Phys. Fluids* 26(2) (2014).
- [2] RAMOS, E. M; DARZE, G. M.; NASCIMENTO, F. R. T; FACCINI, J. L. H.; GIRALDI, G.A. Comparison of dynamic mode decomposition and deep learning techniques for two-phase flows analysis, *Flow, Turbulence and Combustion* (2020).