Comparison of dynamic mode decomposition and deep learning techniques for two-phase flows analysis

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Dynamic mode decomposition (DMD) and deep learning are data-driven approaches that allow a description of the target phenomena in new representation spaces. This fact motivates their comparison in the analysis of flow data, generated through experimental setups and numerical simulations. The focused application is the processing of high-speed videos of horizontal two-phase stratified and slug flows regimes. Henceforth, in this work, we consider the traditional DMD, the sparsity-promoting DMD (SPDMD) and, in the deep learning context, we select an unsupervised convolutional autoencoder (CAE). In this avenue, it becomes imperative to compare DMD and deep learning with respect to: computational complexity of target techniques (Tab. 1); reduced order modeling versus data representation (Tab. 1); data set necessary to compute the dynamic modes and deep learning training (Tab. 1); the preservation of the phase interface in the DMD and CAE space (Fig. 1, Tab. 1 and Tab. 2); data synthesis (Fig. 2 and Tab. 1). In general, the results favor DMD in the considered applications.

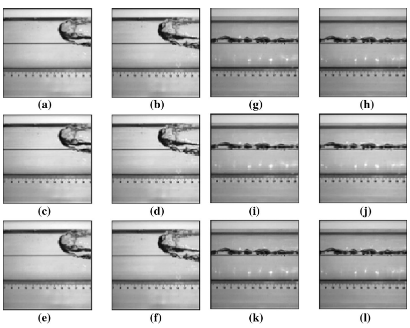

Figure 1. **a**,**b** Original slug frames. **c**,**d** Corresponding reconstructions obtained with the CAE. **e**,**f** Slug frames reconstruction using DMD. **g**,**h** Original stratified images. **i**,**j** Corresponding CAE reconstructions. **k**,**l** Reconstruction of stratified images through DMD.

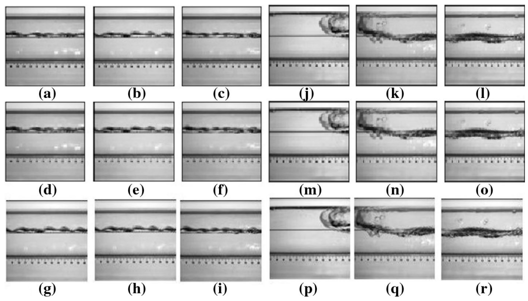

Fig. 2. **a**–**c** Interpolated images for stratified frames. **d**–**f** Images obtained in the decoder output for interpolated stratified feature maps. **g**–**i** Reconstruction of interpolations in DMD space. **j**–**l** Slug frames obtained through interpolation in the image space. **m**–**o** Decoder output for interpolated slug samples in latent space. **p**–**r** Reconstruction of interpolations in DMD space.

Table 1. (a) Computational complexity; (b) reduced order modeling; (c) data representation for pattern recognition; (d) data set necessary to compute the dynamic modes and deep learning training; (e) the preservation of the phase interface in DMD and CAE spaces; (f) void fraction preservation; (g) synthesis of new data samples.

	(a)	(b)	(c)	(d)	(e)	(f)	(g)
DMD	G	E	P	G	E	E	E
CAE	P	P	E	G	G	G	G

E-Excellent, G-Good, P-Poor

Table 2. Time-averaged void fraction for slug and stratified flows.

	Slug	Stratified
Original	0.3551	0.4146
DMD	0.3554	0.4143
CAE	0.3555	0.4206

References

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