

# CRITICAL EVALUATION OF FEATURE DETECTION ALGORITHMS BASED ON MODAL DECOMPOSITION METHODS

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## ABSTRACT

Various modal decomposition techniques have been developed in the last decade [1-11]. We focus on data-driven approaches, and since data flow volume is increasing day by day, it is important to study the performance of low order algorithms.

In this work we compare the performance and feature detection behaviour of eight different algorithms (based on Proper Orthogonal Decomposition [1-3] and Dynamic Mode Decomposition [4-11]) on three data set testcases taken from fluid dynamics. The datasets considered (the velocity field of laminar wake around cylinder at  $Re_D = 100$ , the pressure field of turbulent jet at  $Re_D = 10^6$ , and velocity field of three dimensional transient wake around cylinder at  $Re_D = 280$ ) represent different flow regimes.

The performance of these algorithms is thoroughly assessed concerning both the accuracy of the results retrieved and the computational performance.

From this assessment, those techniques that are potentially better suited for the applications are identified and once the best algorithms have been selected for each test case, which includes laminar flow, transitional flow and turbulent flow, the possibility of parallelizing the algorithms will be studied with a final objective: to enable data-driven analyses of industrially relevant fluid mechanical problems.

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