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Advanced Collapse Clustering Algorithms for Numerical Cavitation Erosion Prediction

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Abstract Cavitation erosion refers to severe material damage caused by collapsing vapor structures near walls. During the collapse of vapor structures, high intensity pressure waves up to several GPa are emitted that can lead to damage of nearby surfaces. Compressible numerical flow simulations enable the numerical prediction of cavitation erosion by spatial and temporal resolution of such pressure impacts. However, these simulations usually only provide point-based pressure data. To obtain numerical substitutes for cavitation erosion pits, further post-processing steps are required, including clustering methods of the point-based pressure data. Using algorithms, spatially and temporally contiguous areas featuring high pressure are recognized and defined as clusters. In this contribution, we test the applicability of various clustering algorithms in the field of artificial intelligence (AI) and machine learning (ML) for this clustering process. We employ established algorithms as *k-means* and *Density-Based* or *Density-Ratio Based Spatial Clustering of Applications with Noise* (*DBSCAN*, *DRSCAN*). The clustered data and the performance of the clustering process are compared with a problem-specific, physically motivated algorithm. Additionally, the simulation results reveal new insights into the spatial and temporal distribution of potentially erosive events.

Keywords: cavitation erosion prediction, pit size, numerical simulation, artificial intelligence (AI), machine learning (ML), clustering algorithms

Introduction

Artificial intelligence (AI) and machine learning (ML) are the main drivers of innovation nowadays. In this paper, we want to demonstrate that tools and algorithms from this fast-growing area can be used beneficially for cavitation erosion prediction.

In cavitating flows, vapor-filled cavities are formed, which later implode emitting intense shock waves and potentially damaging nearby surfaces. In the research group Gas Dynamics at the TU Munich, we investigate cavitating flows and their cavitation erosion potential using fully compressible 3-D simulations of cavitating flows. For the prediction of possible cavitation-induced material damage, we record pressure peaks at surfaces and afterward cluster data points together to physical erosion pits. Until now, a simple flood fill algorithm with spatial and temporal criteria has been used for the clustering. In this contribution, clustering algorithms from ML frameworks are applied to the point-based pressure data and the results are compared to those of a physically motivated flood fill algorithm.

Problem description

We have performed fully compressible numerical simulations of a cavitating jet eroding a target plate (specimen) considering varying pump pressures (p_{in}). The simulation set-up is similar to the experiments conducted by e.g. Fujisawa et al. [1, 2]. Figure 1 depicts the set-up and the erosion on the target. For the simulations we have used our in-house flow solver CATUM (CAvitationTechnical University Munich), which has been successfully validated for cavitation erosion prediction [3, 4], cavitating multi-component flows [5–7], cavitation dynamics [8, 9], and bubble collapses [10]. Viscous effects are considered and the spatial resolution especially resolves the wall-near region with cells of a minimum height of 3 μm, resulting in a grid of about 40 million cells.

Using special algorithms, we monitor and output the hydrodynamic pressure in the near-wall cells. Based on this data, we generate numerical erosion pit data of plastic surface deformation. The data set obtained from our simulations can be interpreted as a 3-D set with the hydrodynamic pressure p as a function of the spatial surface coordinate y, z and the time t as $p = p(y, z, t)$. A representative data set is depicted in Fig. 2.

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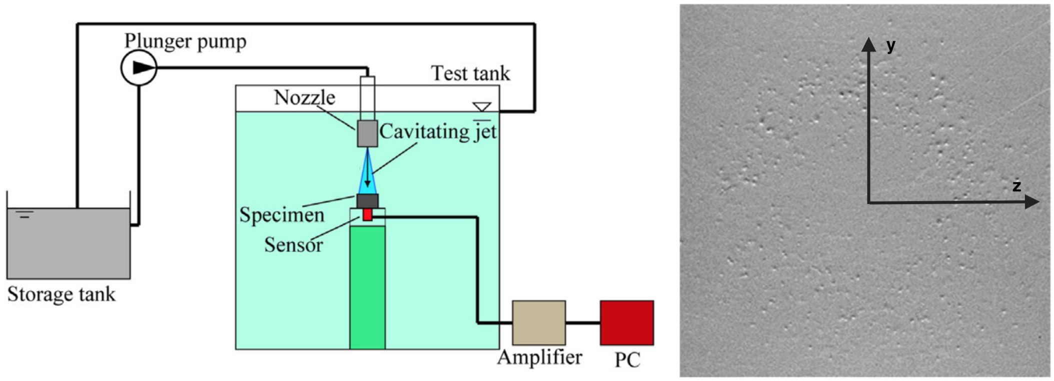


(a) (b)

Figure 1. Considered configuration in (a) and erosion on the target plate (specimen) in (b). The coordinate system has been modified to correspond to the presented results. Figures are reprinted from Fujisawa et al. [2] with permission granted by Elsevier.

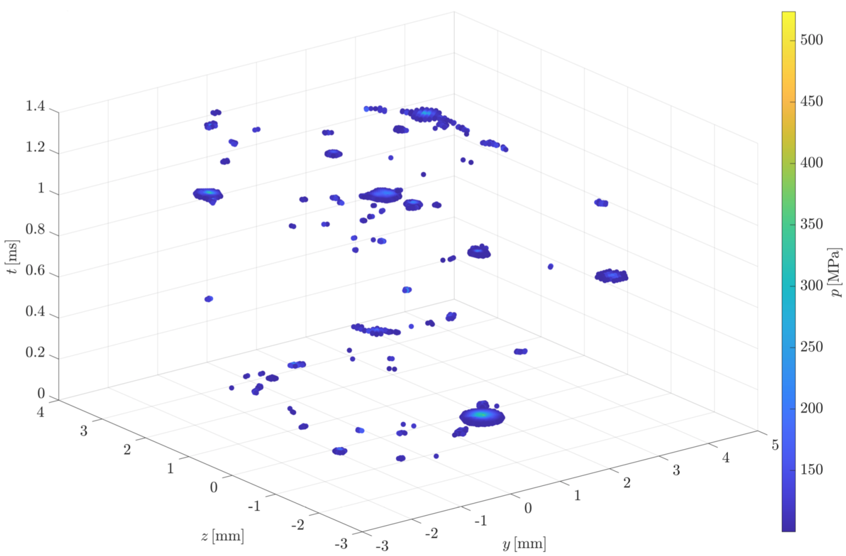


Figure 2. Representative data set of recorded point-based pressure peaks. y and z indicate the target plate (specimen) and t the temporal evolution. Data points are colored by the pressure p.

Method

For the application of clustering algorithms, the first important step involves data preparation. In the considered application, this step consists of filtering the output data by a threshold pressure p_{th}, chosen as $p_{\mathrm{th}} = 100\,\mathrm{MPa}$, and scaling the time. As mentioned above, the data set can be interpreted as a 3-D set with $p = p(y,z,t)$. For generic clustering algorithms, the data points should have comparable distances in each dimension. Since temporal and spatial dimensions of a collapse event are on different scales (µs and mm), the time axis is scaled accordingly here.

Then, the point-based pressure data is clustered, where we applied the following algorithms:

(i) *Physically motivated simple clustering (PMSC)* (Trummler, 2018 [4]):
An engineering approach with a problem-specific algorithm using a simple flood fill algorithm.
Taking advantage of the fact that the local pressure maximum of a pit is centrally located (see also Fig. 4), the algorithm starts the search from such a local pressure maximum. I.e. first the data set is

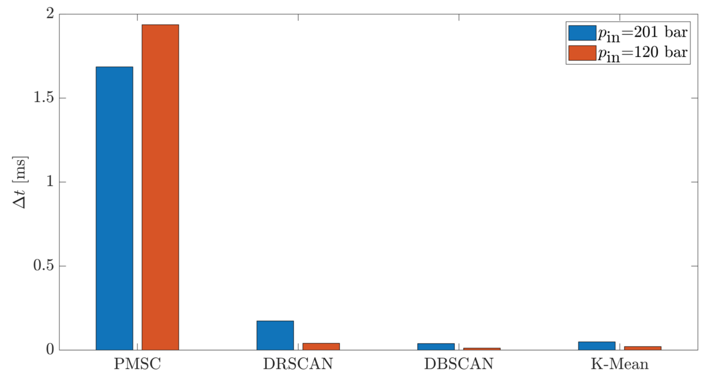


Figure 3. Comparison of the computation time (run time) Δt for the clustering process of two different operating points ($p_{in} = 120\,$bar and $p_{in} = 210\,$bar) using Matlab R2019b on intel core (i5-8265U,1.60GHz).

sorted by descending pressure values. The next value in the list, that is not assigned to another cluster, is used as the starting point for the algorithm. Based on the fact that the spatial distribution is circular (see Fig. 4), the search in spatial direction is also circular. To prevent unphysical merging of pits, additional temporal and spatial limits are employed.

(ii) *k-means clustering* (Lloyd et al., 1956 [11]):
A method of vector quantization, that aims to partition n data points into k clusters by assigning them to the nearest mean. *k-means* is available in standard AI-packages and often employed for ML techniques.

(iii) *Density-Based Spatial Clustering of Applications with Noise (DBSCAN)* (Ester et al., 1996 [12]):
This algorithm clusters points that are close to each other based on a distance measurement (usually Euclidean distance) and a minimum number of points. DBSCAN is a well-known data clustering algorithm commonly used in ML.

(iv) *Density-Ratio Based Spatial Clustering of Applications with Noise (DRSCAN)* (Zhu et al., 2016 [13]):
The DRSCAN represents an improvement of the DBSCAN by modifying the density-based clustering algorithm to do density-ratio based clustering.

Results

Comparison clustering algorithms - Physical plausibility

Since the most important criterion is the physical plausibility of the results, we have first manually checked this. For the considered configuration, the DRSCAN performs best because of its ability to distinguish between pits that are spatially and temporally very close to each other.

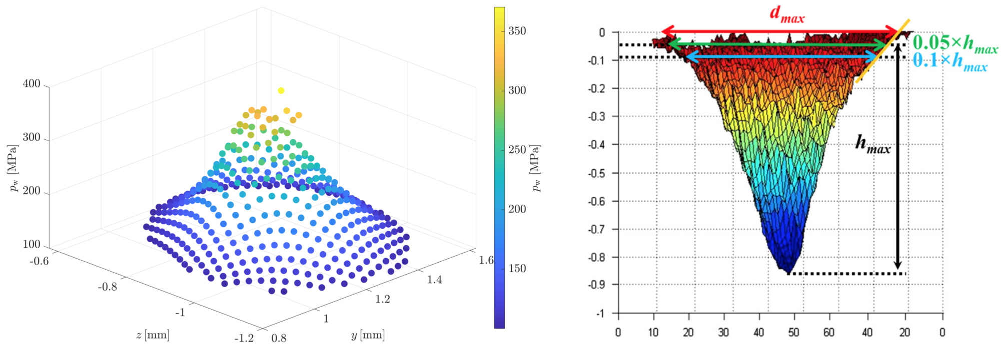
Comparison clustering algorithms - Performance

Figure 3 compares the runtime for the clustering process of two different operating points. ML-algorithms result in a significant performance increase by about 90%. Additionally, using an existing algorithm saves working time as it is not necessary to write a new one from scratch.

Pit formation - Maximum pressure distribution

Figure 4 compares a pit from our simulation results (a) with the experimental data of Roy et al. [14]. The spatial distribution of the maximum wall pressure in our simulation matches the plastic deformation of the experiment. In further studies [15], we have evaluated the correlation of pit radius and pressure maximum and compared the findings with experimental data. Additionally, we have also assessed and compared the cavitation erosion aggressiveness at different operating points.

Furthermore, this analysis allowed us to gain new insights into the duration and temporal evolution of such collapse events, see [15].



(a) (b)

Figure 4. Distribution of maximum wall pressure p_w of one selected pit in our simulation (a) and the experimental results of Roy et al. [14] (b) (reprinted with permission granted by Elsevier).

Conclusion

With this paper, we have successfully demonstrated the great potential of ML and AI algorithms for numerical cavitation erosion prediction. Using an existing algorithm saves code development time and can lead to better performance and higher accuracy.

Clustering point-based pressure data into numerical substitutes of erosion pits can potentially facilitate the numerical prediction of cavitation-induced material damage. First, this reduces the extensive data set of pressure peaks to a smaller, more meaningful, and more sound set of numerical erosion pits that is easier to handle and interpret. Second, this could provide a possible approach for a grid-independent numerical prediction of cavitation erosion. While collapse-induced maximum pressures are strongly grid-dependent [3, 4, 10], number and size of pits could lead to a grid-independent prediction.

In a larger context, the aim is to predict actual material deformation. For this purpose, a functional relationship of hydrodynamic pressure signals (intensity and duration) with the material deformation is necessary and can be obtained, for example, by coupled fluid-material simulations (see e.g. [16–18]) incorporating suitable material models.

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