Detecting In-cylinder Vortex Properties with Comprehensive Clustering Methods

VM458 Project 2 Group 3

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Introduction

In-cylinder flow

- **In-cylinder flow**
  - Complex behavior
  - Cyclic variation
- **Why properties and behavior of in-cylinder flow is important?**
  - Affecting the air-fuel mixture process
  - Affecting the combustion behavior

Review on detecting flow[1]

- **How to detect and analyze in-cylinder flow?**
  - Particle Image Velocimetry (PIV)
  - Computational Fluid Dynamics (CFD)
  - Wind-rose Diagram

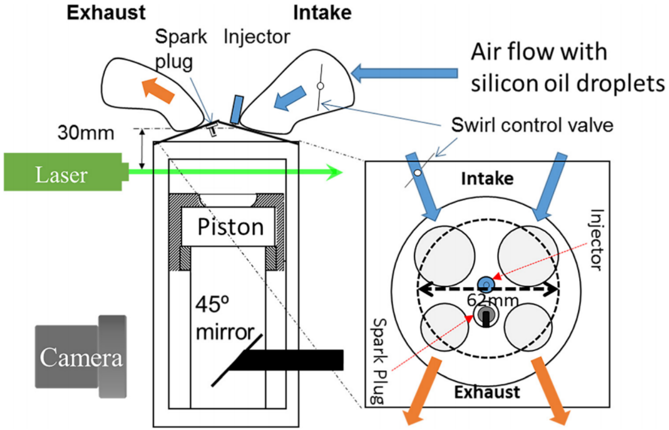


Fig. 1 PIV setup[1]

Cylinder model —PIV— **Raw data**

Raw data — **Velocity map**

Simulation —CFD— **Velocity map** —WR-Diagram— **Vortex center location map**

[1] Zhao, F., Ge, P., Zhuang, H., and Hung, D. L. S., “Analysis of Crank Angle-Resolved Vortex Characteristics Under High Swirl Condition in a Spark-Ignition Direct-Injection Engine,”JOURNAL OF ENGINEERING FOR GAS TURBINES AND POWER,30 November 2017.

Data sets

- **Data sets[1] including:**
  - Velocity map
  - Vortex center location map
  - Number of vortex centers
- **Background:**
  - Medium swirl ratio
  - 100 cycles
  - Every 2 crank angle degree (CAD) fr (-60°)

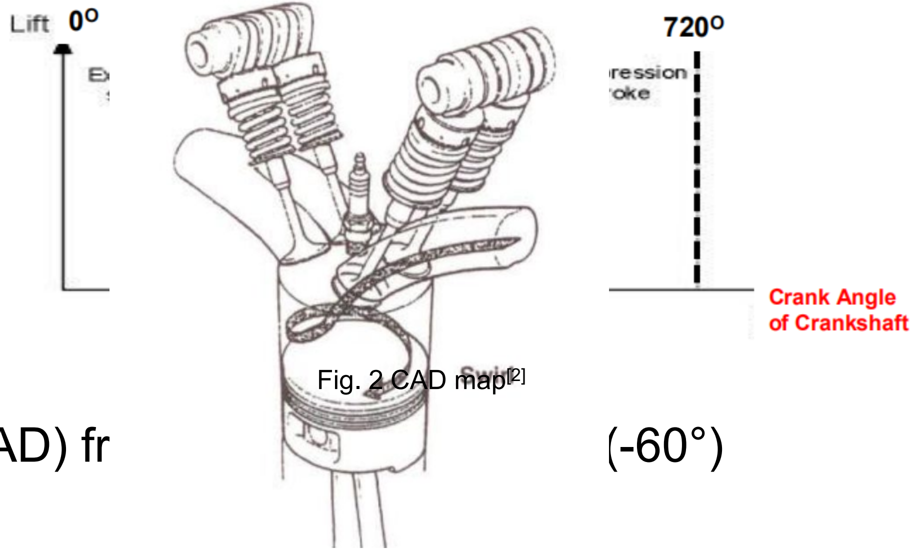
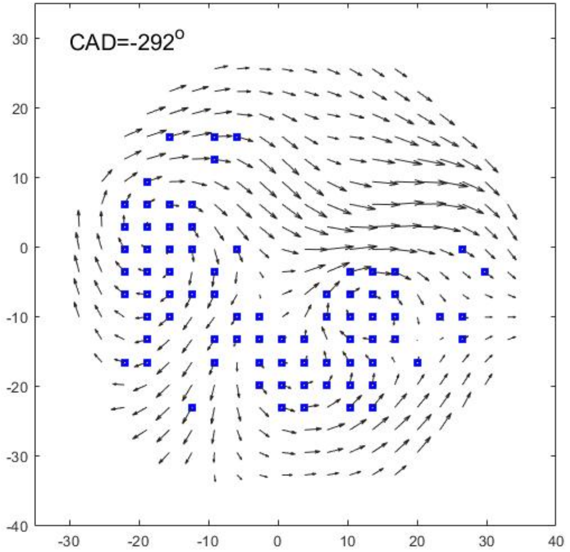


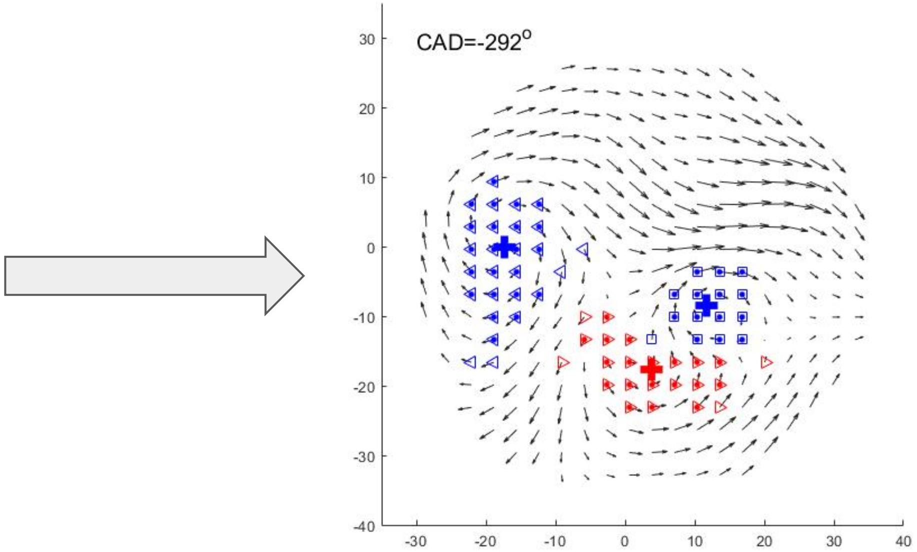
Fig. 2 CAD map[2]

Fig.1 Swirl in the engine[3]

[1]: TA Group, 2020, VM458 Project 2: Machine Learning + Automotive Instruction.
[2]: David, H. 2020, VM458 Lecture13.
[3]: J.L. Lumley, Engines An Introduction, P.148-149.

Visualization





Clustering Method[1]

- **Unsupervised machine learning method**
- **Labeling points into different groups**

Method	Requires specified number of clusters	Useful for outlier detection
k-Means Clustering[1]	Yes	No
Density-Based Spatial Clustering of Algorithms with Noise (DBSCAN)[1]	No	Yes
Gaussian Mixture Model[1]	Yes	Yes
Hierarchical Clustering[1]	No	No

[1] https://ww2.mathworks.cn/help/stats/choose-cluster-analysis-method.html.

K-Means

- **Introduction**
  - Pre-set cluster number
  - Random center points
  - Minimizing the sum of distance
- **Parameter**
  - Pre-set total cluster number
  - Way of calculating direction
  - Itration
- **Pro**
  - Straightforward parameter
  - Single level cluster
- **Con**
  - Local optimal choice
  - Not able to detect the outlier
  - Low accuracy for incorrect cluster number
  - Each point assigned to one cluster

Density-Based Spatial Clustering of Algorithms with Noise (DBSCAN)

- **Introduction**
  - Automatically find the multilevel clusters with defined neighbor range and minimum points
- **Parameter**
  - Neighbor range
  - Minimum neighbor points
- **Pro**
  - Detecting the core points, border points, and outliers
  - Separating different clusters
- **Con:**
  - Not able to find center

Gaussian Mixture Model (GMM)

- **Introduction**
  - Separating clusters based on normal distribution
  - Covariance structure
- **Parameter**
  - Pre-set total cluster number
  - Diagonal state
  - Covariance state
- **Pro**
  - Each point has chances in different clusters
  - Changeable size and direction of cluster distribution ellipse
- **Con**
  - Not able to detect outlier

Hierarchical Clustering

- **Introduction**
  - Comparing each distance pair
  - Creating multilevel of clusters
- **Necessary Parameter**
  - Way of linkage
- **Pro**
  - Arbitary shape and number of cluster
- **Con**
  - Low efficiency

Objective

- **Detect vortex property and behavior including:**
  - Rotation direction
  - Number of vortex centers
  - Size and track of the vortex
  - Cyclic variation
- **Detect vortex property and behavior:**
  - From offered data sets
  - With multi clustering methods
- **Discuss the advantages and disadvantages of each clustering methods**

Data Processing

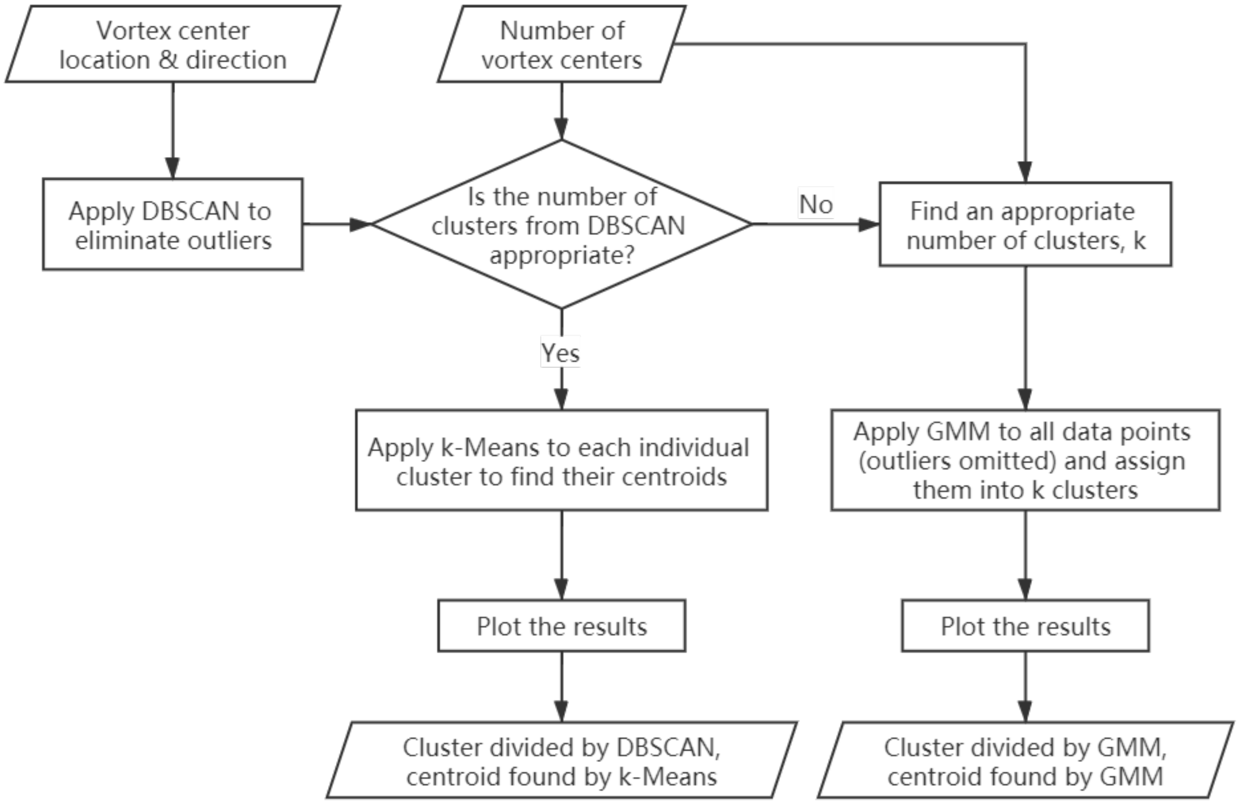
Vortex Detection

- **Methods explored**
  - k-Means, DBSCAN, Gaussian Mixture Model
- **Rotating direction**
  - Provided by data set: 0 for clockwise, 1 for counterclockwise
- **Elimination of outliers**
  - Achieved by algorithm
  - Can be adjusted according to requirement
- **Number of clusters (vortex centers)**
  - Algorithm result or provided by data set

Vortex Detection

Trial	Method	Way to find number of clusters	Accuracy and problems
1	K-Means	Average of given data	Accuracy < 70%
2	K-Means	Manually picked according to CAD	No defined criteria Not able to eliminate outliers
3	DBSCAN	DBSCAN	Not able to find centroid
4	K-Means	DBSCAN	K-Means gives locally-optimum solution
5	DBSCAN & k-Means	DBSCAN	Accuracy around 90%
6	DBSCAN & k-Means & GMM	DBSCAN & average of given data	>95% accuracy

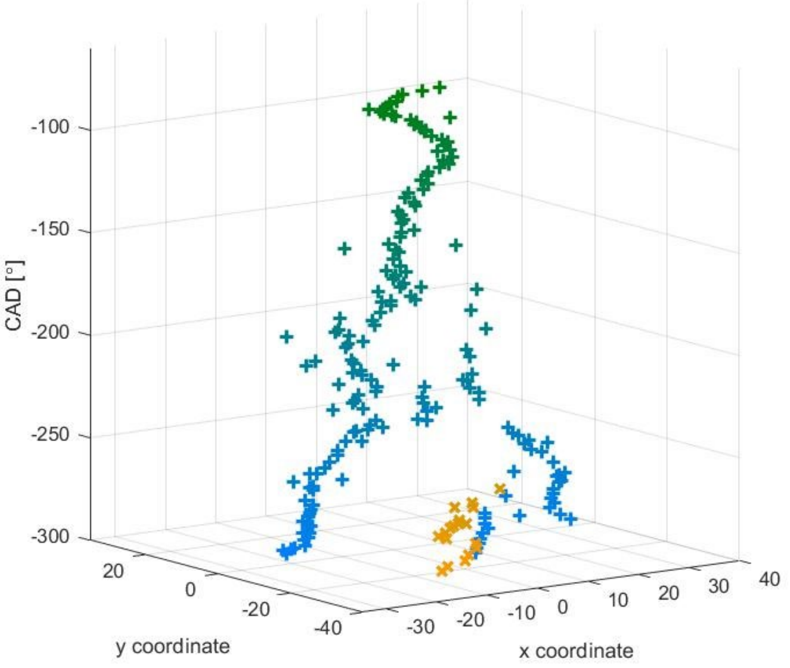
Flow Chart

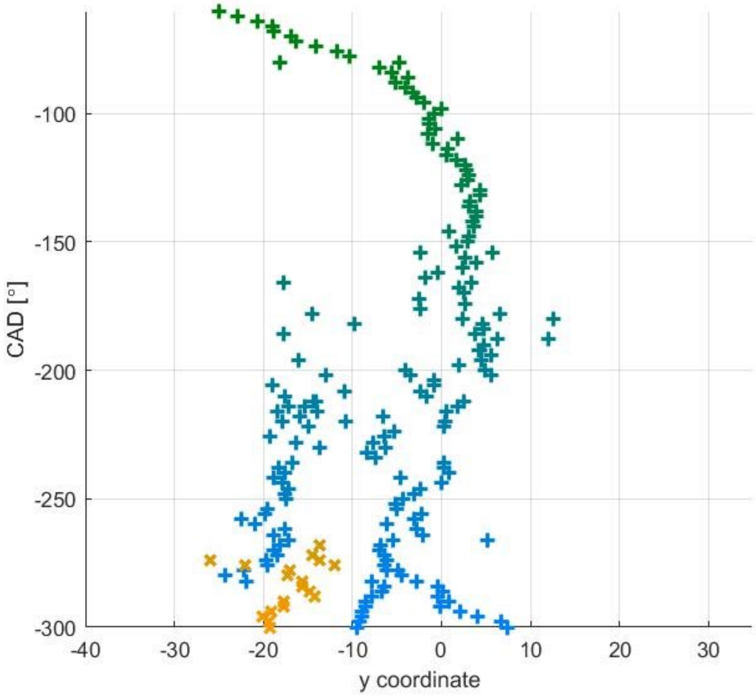

Vortex center location & direction
Number of vortex centers
Apply DBSCAN to eliminate outliers
Is the number of clusters from DBSCAN appropriate?
No
Find an appropriate number of clusters, k
Yes
Apply k-Means to each individual cluster to find their centroids
Apply GMM to all data points (outliers omitted) and assign them into k clusters
Plot the results
Plot the results
Cluster divided by DBSCAN, centroid found by k-Means
Cluster divided by GMM, centroid found by GMM

Results

Vortex Track

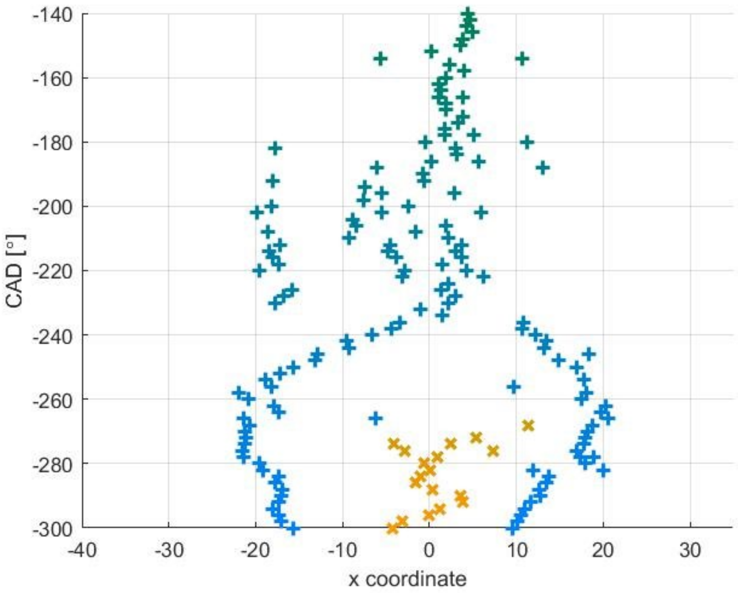
- **Track of vortex centers with CAD as z-axis & CAD-y plot**
    - Clokcwise: blue & green, counterclockwise: yellow

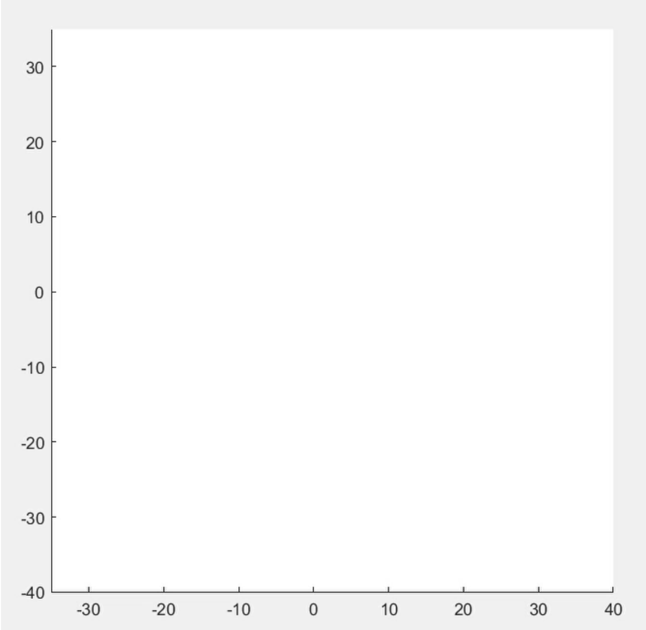




Cyclic Variation

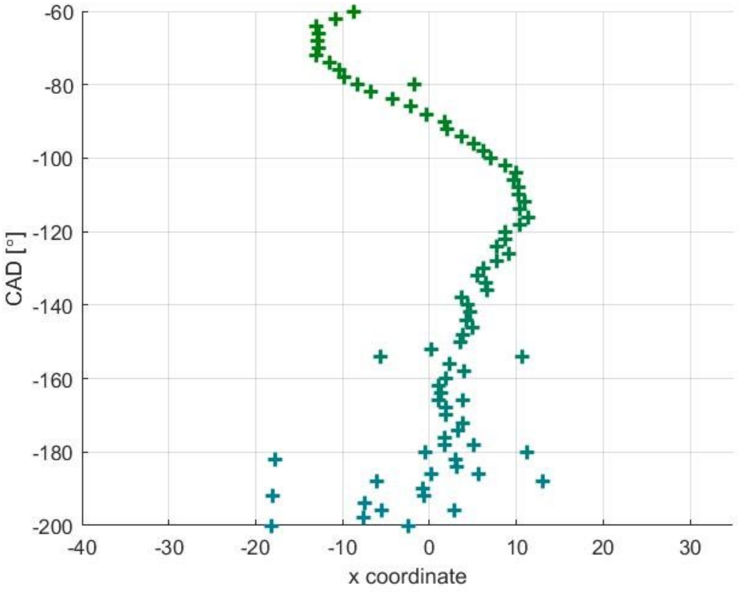
- **-300 CAD to -180 CAD**
  - Counterclockwise vortex vanishes
  - 2 clockwise vortices start merging, multiple clockwise vortices coexist

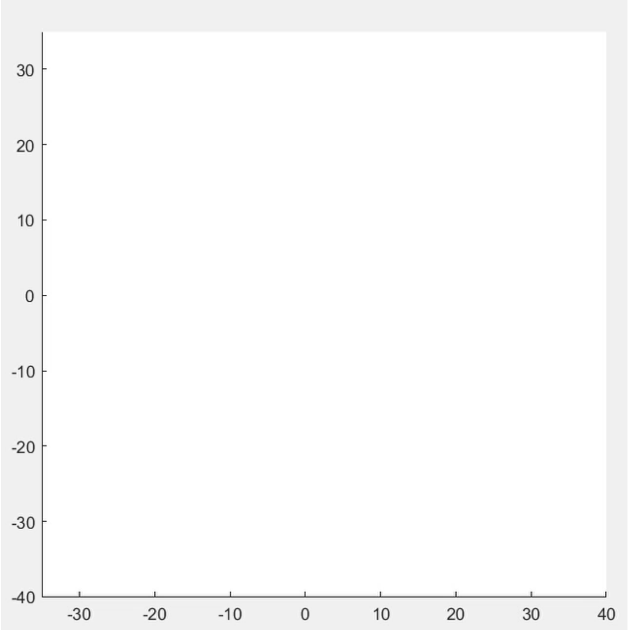




Cyclic Variation

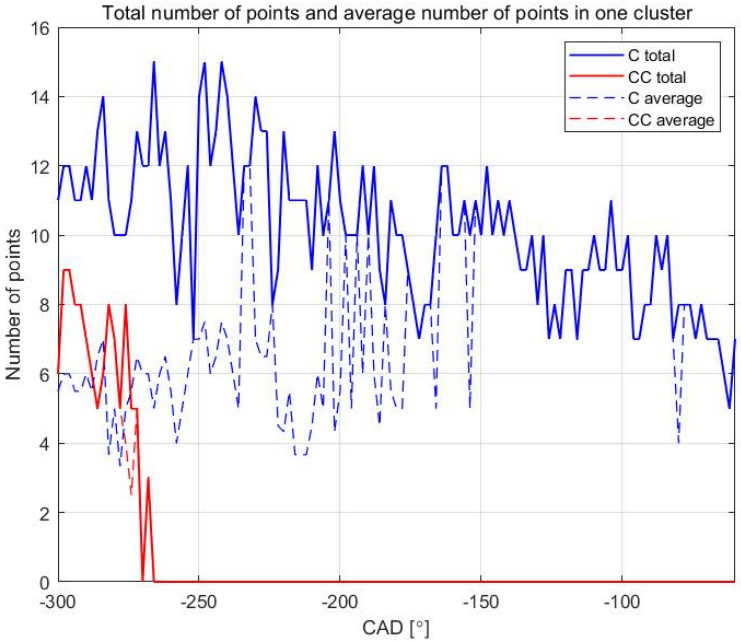
- **-180 CAD to -60 CAD**
  - Clockwise vortices merge at center
  - Single clockwise vortex moves from center to border

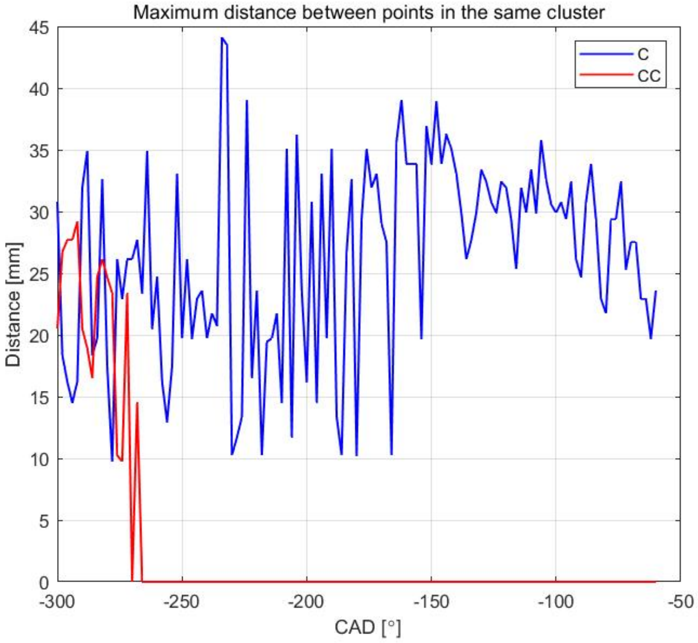




Cyclic Variation

- **Number of points & max distance**
  - C for clockwise, CC for counterclockwise





Discussion

Understanding of algorithm

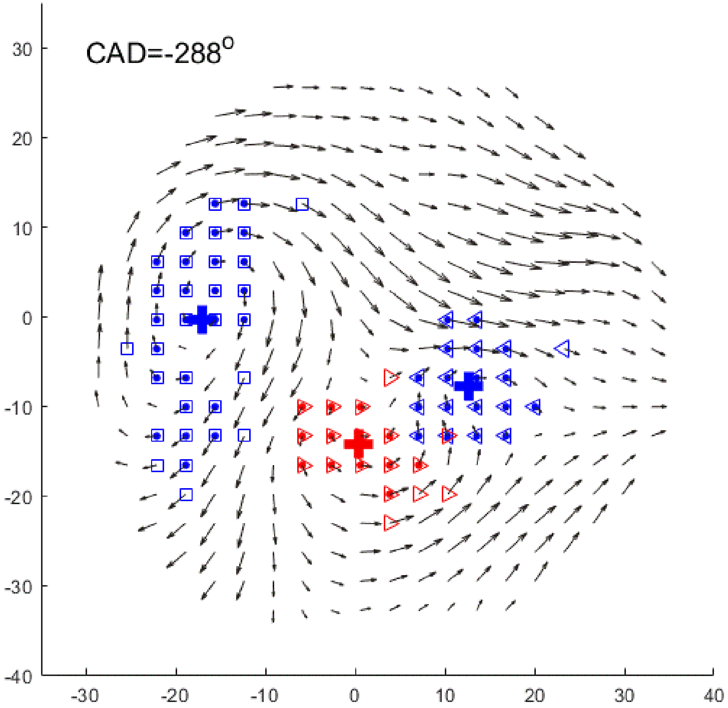
- **The most important parameters of clustering algorithms**

  (a.k.a, the input parameters)

Method	Number of clusters, k	Chosen metric norm	Min neighboring number, n	Neighboring range, ε
K-Means	Yes	Yes	No	No
GMM	Yes	Yes	No	No
DBSCAN	No	Yes	Yes	Yes

Understanding of algorithm

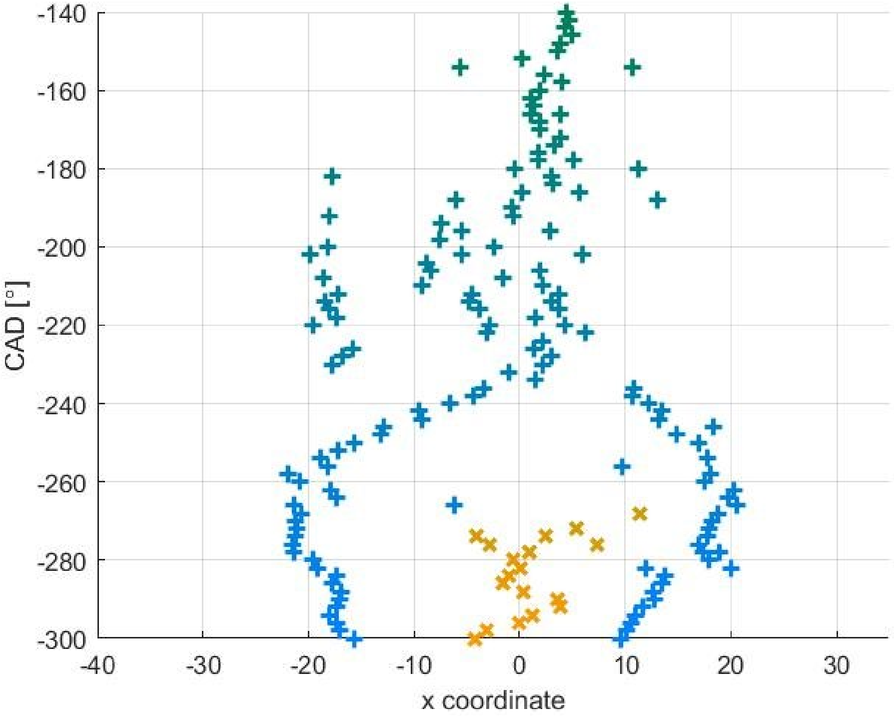
- The selection of “norm” : metric norm
  - Euclidian distance -> “City block” distance
- The selection of appropriate cluster number: k
  - DBSCAN can determine k (for reference only)
- The selection of appropriate neighboring range: ε and number: n
  - A subtle problem: try and error



Physical analysis of variation

-300 CAD ~ -180 CAD

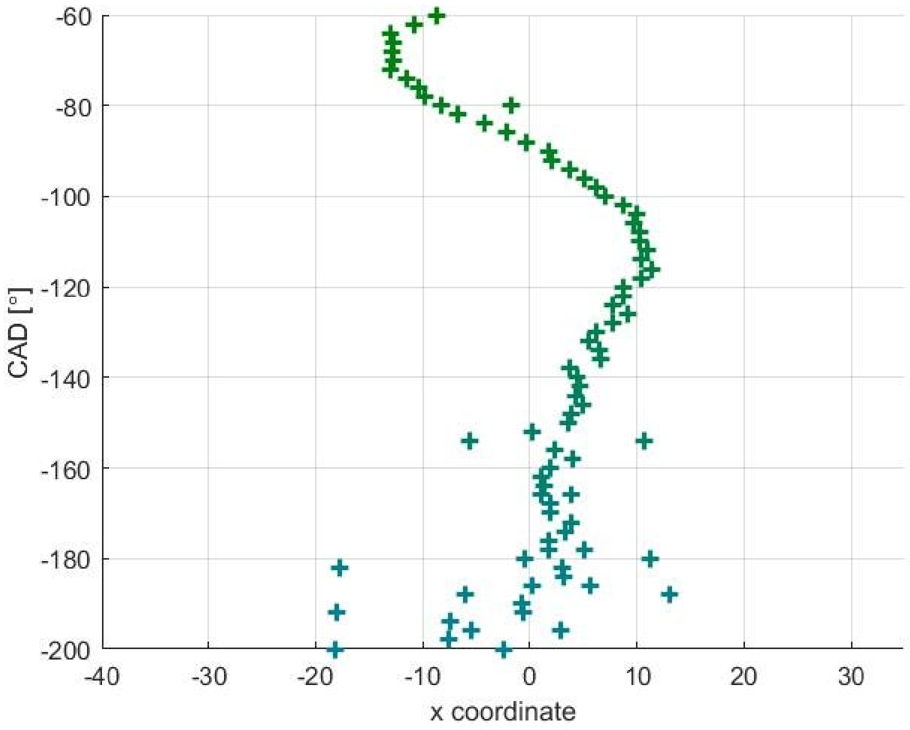
- Intake valves are open.
- The drawback vortex decays fast.
- The two major vortices begin to merge and move to the center together.
- The flow field is chaotic at the end of intake stroke when the vortices are incompletely merged.



Physical analysis of variation

-180 CAD ~ -60 CAD

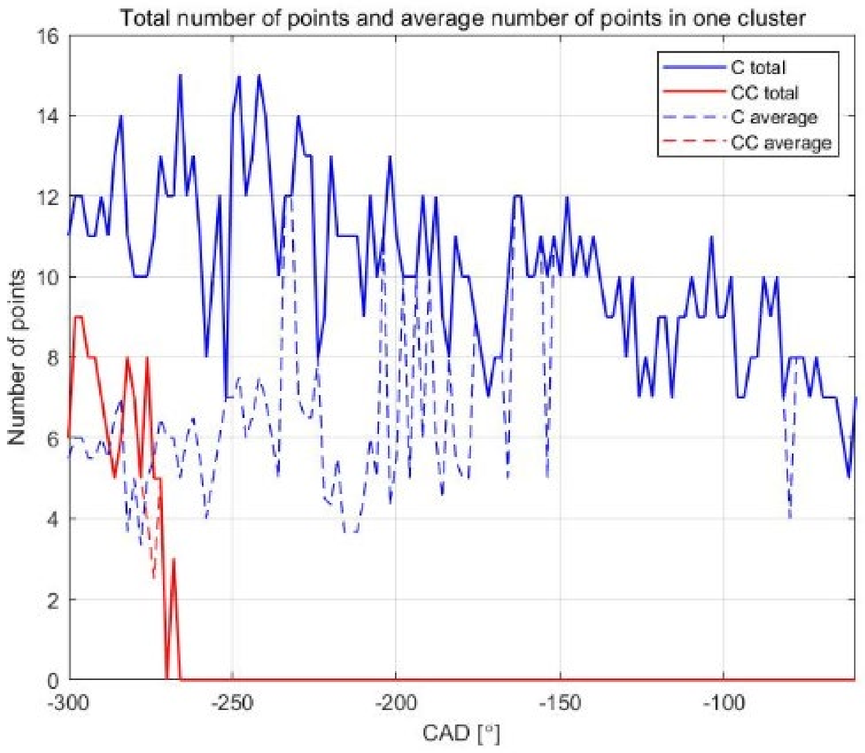
- Intake valves are closed.
- The two vortices merge to one vortex after the closure of valves.
- When the compression stroke starts, the vortices begins to merge and the flow field converges in a short time.
- During the compression stroke, the flow field behaves stable.



Physical Analysis of variation

Variation in size

- The size is counted with the number of core points.
- The average size of a clockwise vortex is larger than the counter-clockwise's .
- Mean of the average size is about 8 core points, variance of average size is quite large



Physical Analysis of variation

Variation in number

- Clockwise:

  Mostly 2 vortices at the beginning→

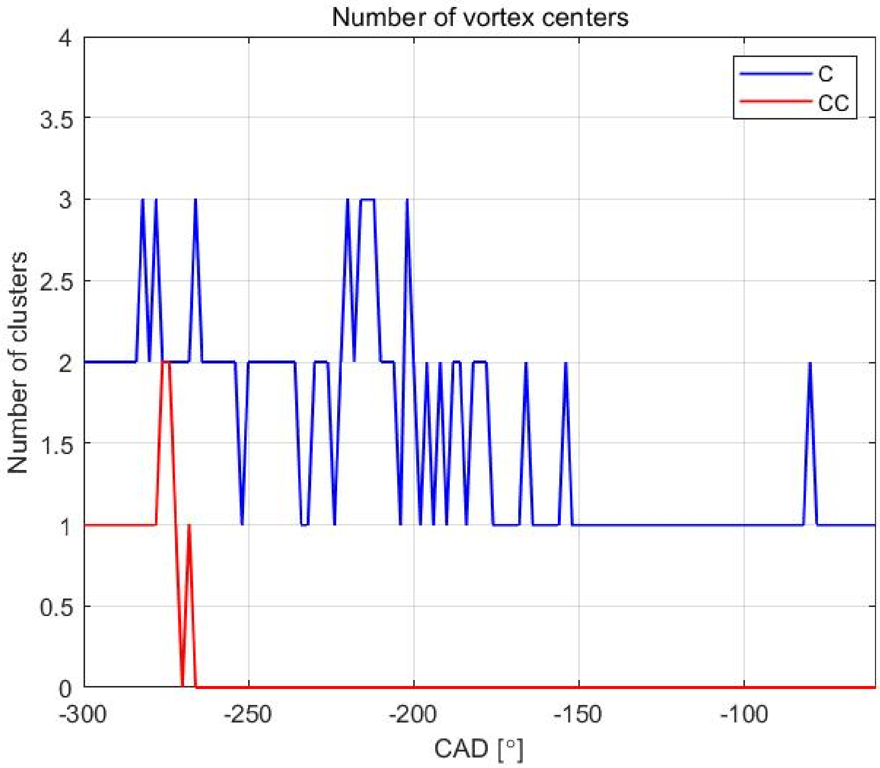
  Varying greatly between 1, 2,and 3 vortices at the end of intake stroke→

  Mostly 1 vortex after compression stroke begins.

- Counter-clockwise:

  Mostly 1 vortex at the beginning →

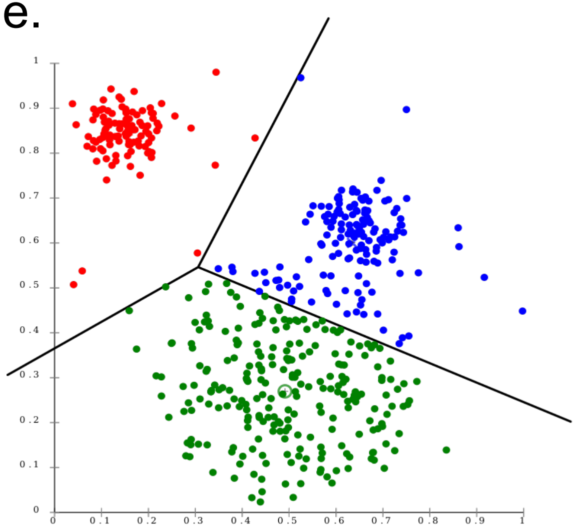
  Mostly 0 vortex after a short time.

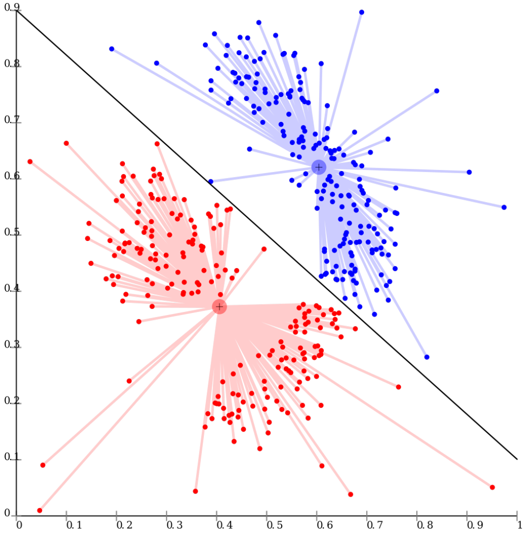


Other applications

Clustering Methods

- The anticipation of motion of cloud and wind for weather forecasts.
- The identification of the state of the machine in predictive maintenance.
- The artificial intelligence that can “guess what you like” with big data and users’ profile.





Conclusion

Conclusion

- **We have detected:**
  - Rotation direction
  - Number of vortex centers
  - Size and track of the vortex
  - Cyclic variation

  with three clustering methods, and analyze the physical meaning of the vortex behavior and properties.

- **We have discussed the advantages and disadvantages of each clustering methods, and combined them to get better clustering behaviour.**
- **We have found other potential area to apply this method.**

Q&A