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A hybrid computer vision and machine learning approach for robust vortex core detection in fluid mechanics applications

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Abstract

Vortex core detection remains a challenging topic within the field of computational fluid dynamics (CFD). Local methods, such as the Q, delta, or swirling-strength criterion, are commonly used to detect vortices and these methods are entirely based on the local velocity gradient tensor. Results have shown that reasonable estimates can be obtained with these methods, however, at the same time, these methods produce a significant number of false positives and negatives. User-defined tuning parameters are introduced to keep the number of false positives and negatives in balance, but this requires knowledge of the vortices and thus does not present a robust and self-contained approach. We recently proposed a novel computer vision approach where we have trained a convolutional neural network (CNN) to look at line integral convolution (LIC)-based streamline plots. We showed that this approach is capable of accurately predicting the regions where vortices reside, and we were able to reduce the false positives and negatives to zero. Furthermore, we showed the universality of this approach by successfully applying our trained CNN to a different test case for which it has not been trained and which featured different vortical structures (generated through a different physical process). The CNN-based approach is limited in the sense that it is only able to predict the bounding boxes of vortex cores, but not the exact location of the vortex core itself. Therefore, we propose a hybrid machine learning and computer vision approach in this study, where we first identify areas of vortical structures using computer vision to which we add a layer of machine learning to find the vortex core within the vortex region. We test different sets of input parameters for both the hybrid and pure machine learning approach, starting with just the primitive variables (velocity and pressure), and adding more derived quantities (velocity gradients, pressure gradients, Q-criterion, vorticity, and magnitude of vector quantities). Comparing the hybrid with the pure machine learning approach applied to the full flow field, we show that the hybrid approach reduces the training time for all tested cases up to a factor of 2. We also find that using the primitive variables along with their derivatives provide fewer false positives and negatives using the hybrid approach. At the same time, using the variable set with all possible inputs does not provide a more accurate prediction of vortex cores and thus we demonstrate that our hybrid computer vision and machine learning approach is an effective way to reduce false positives and negatives entirely using just the primitive variables and their derivatives.

Key words: *machine learning; computer vision; vortex core detection; fluid mechanics*

1 Introduction

Two types of algorithms are commonly used to detect vortices, local and global. The local method is based on the decomposition of the local velocity gradient tensor such as Q criterion, delta criterion, Lambda 2 criterion, and swirling-strength criterion [1]. These techniques could acquire reasonable estimates, yet, at the same time, these techniques generate a substantial number of false positives and false negatives. To control the number of these false positives and negatives, the user should set appropriate parameters which lead to poor robustness. The Global vortex detection methods are typically accomplished through streamlines to detect vortex regions. Generally, global methods are more robust than local methods, but they use neighboring cells to identify vortical flows, which adds to their computational time. Local methods, on the other hand, require users' input who have certain specific knowledge about the field, making them inappropriate to automatically detecting vortex cores. Due to this, both local and global detection methods have weaknesses and cannot provide fully robust and reliable results.

To address this problem, we present a hybrid computer vision and machine learning approach in this study to detect vortex core. Initially, we employed computer vision to identify the areas of vortical structures, then we apply machine learning to identify the vortex core within the vortex region. You Only Look Once (YOLO) algorithm [2] has been used in the computer vision part to identify the regions where the vortex cores are located. Then, machine learning is added on top where this hybrid approach of Computer Vision (CV) and Machine Learning (ML) will add new dimensionality. machine learning is a set of features that can be used not only to identify the vortices in general but also to detect the vortex core, which is an important application in fluid mechanics. The benefit of tracking these vortices is to know how the flow is developing. The machine learning part is performed using Keras, which is a deep learning Application Programming Interface (API) acting as an interface for TensorFlow.

2 Problem description

To deal with the issues in traditional vortex identification methods, we propose a hybrid computer vision and machine learning approach.The initial step of identifying the vortex region takes place using computer vision. This is followed by machine learning to find the vortex core inside the vortex area. To examine the effectiveness of this model, we use the Taylor-Green vortex problem. The Taylor-Green vortex flow is simulated using Large-Eddy Simulation (LES) at Reynolds number 1600 and the initial conditions are taken from [3]. The discretization of the Taylor-Green vortex was achieved using a uniform mesh having a resolution of 64^3 with a time-step of $\Delta t^* \approx 0.06$, and a total of 335-time steps are required to advance the solution from $t^* = 0$ to $t^* = 20$ at $CFL = 0.6$. In this case, t^* is a non-dimensional time, which is defined as $t^* = tU_0/L$. Figure 1 shows the contour velocity plot at the beginning ($t^* = 0$) and final time step ($t^* = 20$).

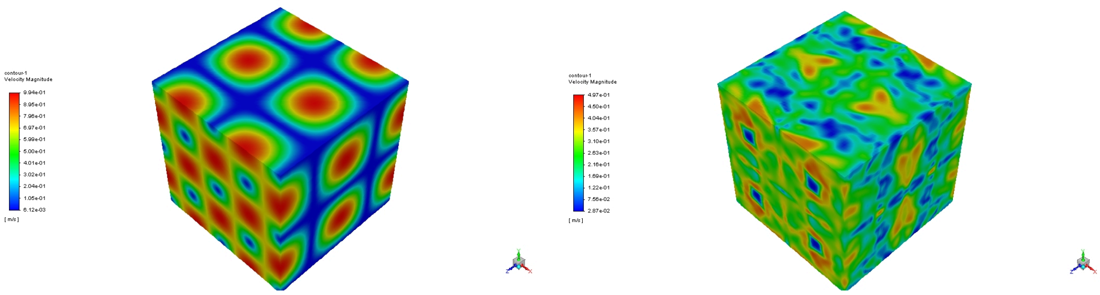


Figure 1: Contour velocity plot. The left-hand side at the beginning initial state and the right-hand side at the end time step.

For each time step, we exported the velocity vectors on the symmetry planes along the x-, y-, and z-axis. Then, line integral convolution (LIC) streamline images were produced using ParaView, and 100 of the images were labeled manually to serve as a training dataset input for the YOLO computer vision framework [4]. Our recent study has demonstrated that this method can accurately predict the regions of vortices and reduce false positives and negatives entirely. After detecting the areas of vortical structures using computer vision, we apply machine learning to locate the vortex core within each vortex region. Within these regions, we obtain the values of different sets of features to train our model using deep learning with TensorFlow and Keras.

3 Results

For testing our model, we choose an ASCII file exported from our test case among the 335 time-steps in the symmetry plane in the x-direction, which is not part of the training data set. Table 1 shows the result of the predicted vortices using our hybrid approaches (computer vision and machine learning) and single approach (pure machine learning) with different input vartiable combinations for the ML part. The variable sets are as follows:

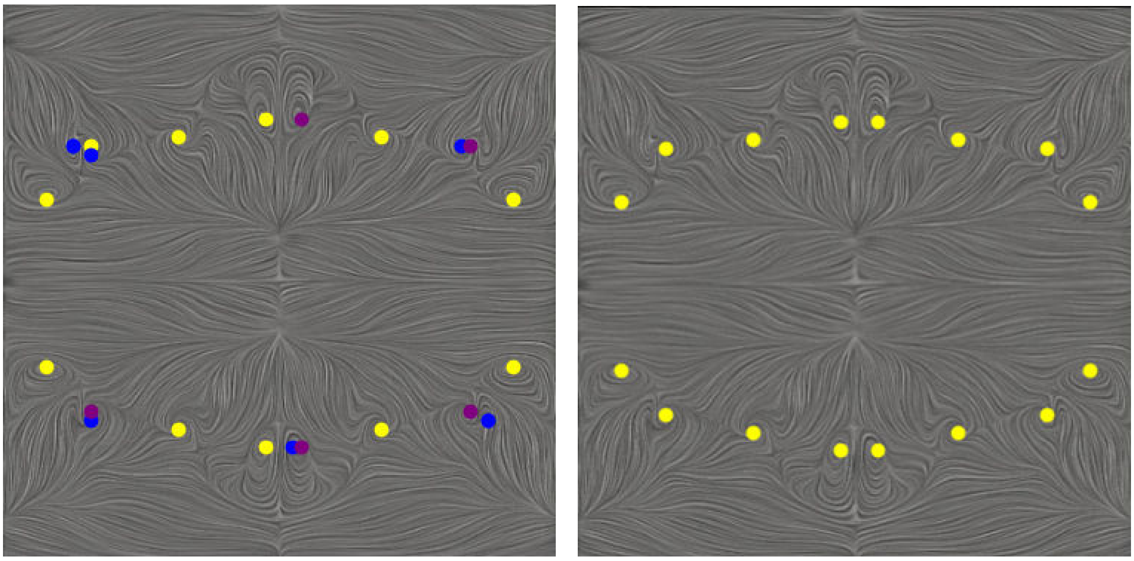
1. x-velocity, y-velocity, w-velocity, velocity magnitude and pressure

2. Set 1 + velocity gradient tensor and pressure gradient
3. Set 1 + u-vorticity, v-vorticity, w-vorticity and vorticity magnitude
4. Set 2 + u-vorticity, v-vorticity, w-vorticity and vorticity magnitude
5. Set 4 + dynamic pressure, normalised Q-criterion and absolute Q-criterion

Table 1: Showing a number of expected and detected vortices for the sample test, as well as comparison of hybrid approaches and a single approach how false positives and negatives reduce as the number of ASCII files in the training data set increases with different Variable sets from 1 to 5 as input features mention above and The computational time is taken for training in both methods.

Test image										
# of files	Variable set	Total vortices	Both approaches			Training time	Single approach			Training time
			TP	FP	FN		TP	FP	FN	
5	1	16	8	11	8	00:42:27	6	5	10	01:39:33
	2	16	11	8	5	00:37:48	10	4	6	01:43:24
	3	16	8	5	8	00:38:28	9	5	7	01:46:18
	4	16	11	3	5	00:42:10	10	5	6	01:53:45
	5	16	12	5	4	00:43:18	11	4	5	01:59:37
10	1	16	8	7	8	01:41:59	7	6	9	02:57:52
	2	16	13	3	3	01:44:38	11	4	5	03:12:14
	3	16	11	5	5	01:46:02	10	2	6	03:20:09
	4	16	12	3	4	01:51:11	12	5	4	03:24:20
	5	16	14	7	2	01:55:28	14	9	2	03:36:43
20	1	16	13	9	3	02:24:50	10	8	6	05:38:34
	2	16	15	2	1	02:40:48	13	4	3	05:42:27
	3	16	14	1	2	02:33:17	12	6	4	05:40:01
	4	16	15	3	1	02:47:10	13	2	3	05:49:52
	5	16	16	0	4	02:56:19	15	3	1	05:54:11
25	1	16	15	4	1	03:11:16.	13	2	3	07:53:40
	2	16	16	0	0	03:23:38	16	0	0	08:00:03
	3	16	15	0	1	03:15:19	13	0	3	07:58:06
	4	16	16	0	0	03:48:58	16	0	0	08:13:13
	5	16	16	0	0	04:04:18	16	0	0	08:34:01

Table 1 shows the result of using 5, 10, 20 and 25 different ASCII files for the machine learning step for both the pure and hybrid learning for each variable set. We see that using just five ASCII files as a dataset, the false positive and negative rates remain high for both approaches, and just using machine learning gives fewer false positives. At 20 ASCII files with variable set 5, our hybrid approach produces zero false positives, and at this point, with half the training time, the hybrid approach is starting to produce less false positives than the single approach. Once the training dataset has 25 ASCII files, neither approaches produce false positives or negatives for 2, 4, and 5 variable sets. Hence, we can conclude that using gradients or variable set 2 always produces better results than using variable set 1. Traditional methods use only velocity gradient tensors, whereas we also utilized absolute velocity and pressure components. In Figure 2, we show the results of using the hybrid approach for five ASCII files on the left, and 25 ASCII files on the right. The yellow dots depict where a vortex core has been correctly detected (true positives), and the purple dots indicate where a vortex core has been wrongly identified (false positives). The blue dots represent when a vortex core has not been identified (false negatives).



Variable set : 2
Number of ASCII files: 5

Variable set : 2
Number of ASCII files: 25

Figure 2: The figures show the result of using 5 ASCII files on the left hand side and 25 ASCII files on the other side as training data set for the second variable sets where the yellow dots are shown the right prediction of actual vortex cores(true positives) and purple dots are false positives and the blue dots indicate the false negatives .

4 Conclusions

Detection of vortex cores within computational fluid dynamics (CFD) is still a challenging task. In this project, we introduce a hybrid computer vision (YOLO v3 algorithm) and machine learning (TensorFlow, Keras) approach to detect the vortex core of the Taylor Green Vortex. The first step is to employ computer vision to identify the region where the vortices are in order to present only vortical flow patterns to the machine learning step, which is executed after regions of vortices are identified to extract the location of the vortex core. In this study, we have shown that velocity and pressure are essential information to predict the vortex cores correctly and that we can reduce the rate at which the false positives and negatives are reducing by incorporating gradient informations of the velocity and pressure.

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