Application of computer vision and neural network analysis to study the structure and dynamics of turbulent jets

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Abstract. In this paper we solved the problem of detecting and detailed analysis of the characteristics of coherent structures in non-swirling and swirling turbulent jets from the 3D PIV experiment and DNS modelling database. To solve the problem intellectual approaches of computer vision based on deep neural networks were applied. It is shown that with the use of a generative competitive neural network, it is possible to reconstruct the structure and dynamics of a turbulent flow with an increased spatial resolution, which is important for analysis and interpretation. The approach is based on a modification of the loss function, which minimizes the residual part of the hydrodynamic equations (the continuity equations and the Poisson equation) for the reconstructed data. It is shown that generative models are more effective in the reconstruction of high moments of turbulent flow than conventional methods POD and DMD. Using a fully convolutional neural network, an automatic segmentation of the turbulent jet flow region and the external environment based on instantaneous velocity and pressure fields was carried out. For a swirling jet, the area of reversed flow is identified. It is shown that the complex of the developed machine learning algorithms successfully copes with the localization of coherent structures, the detection of their trajectory, characteristic size and phase propagation velocity. The obtained new fundamental information is important for a deeper understanding of the role of vortex structures in mixing processes in a jet flow. The developed complex of algorithms for the identification and analysis of characteristics of coherent structures can be applied to a database of measurements and numerical simulation of a wide class of hydrodynamic flows.

1. Introduction

It is well known that large-scale vortex structures play an important role in the processes of heat and mass transfer in jet flows. In this regard, the study of their characteristics is an important task both from a fundamental and from a practical point of view. The use of the non-contact optical method PIV (Particle Image Velocimetry) and the method of direct numerical simulation DNS (Direct Numerical Simulation) allows to obtain detailed information on the distribution of the instantaneous velocity field in turbulent flows. However, often, a large amount of data makes it difficult to analyze and interpret the results. Thus, the obtained primary information requires a detailed analysis using automatic procedures for the identification of the characteristic flow features. The development of intelligent data analysis methods and the growth of computing power made it possible to use neural network algorithms to study the structure and dynamics of turbulent flows. There is a large number of examples of machine learning methods being used, for example, in many aviation problems of simulation of empirical phenomena, malfunction diagnosis, and control [1-4]. In this paper, we solved...
the problem of detecting and detailed analysis of the characteristics of coherent structures in non-swirling and swirling turbulent jets from PIV experiment and DNS modeling database. To solve the problem, intellectual approaches of computer vision based on deep neural networks were applied. Now, this actual topic is practically not developed in the literature.

In many literary sources computer vision problem statements of classifying and detecting objects are known. In the task of classifying objects, we want the model to determine which individual object or scene is present in the image. Therefore, the classification operates on a high level of abstraction. The task of detecting objects is also well known, where we are trying to find and classify several objects in the image, drawing bounding boxes around them, and then classifying what is in this field. Therefore, detection takes place at the middle level, where we have quite useful information, but it is still rather rough, because we define only the bounding box and do not get an accurate idea of the object shape. Semantic segmentation is the most informative of these three tasks, because we try to classify each pixel in the image. In the literature there are many works on semantic segmentation, for example [5-11]. One of the efficient algorithms for semantic segmentation are fully-convolutional neural networks (FCN) [5]. A fully convolutional network (FCN) learns the mapping from pixels to pixels without extracting proposals of regions unlike region-based models such as Mask R-CNN [7]. The FCN pipeline is a continuation of the classic convolutional neural networks (CNN) (see figure 1). The basic idea is to force classic CNN to take an image of arbitrary size as input. The limitation of CNN is to take images of a fixed size due to the use of fully connected layers that are fixed.

In this paper, the architecture of the deconvolution network [5] was used to segment the velocity and pressure fields.

Generative adversarial neural networks (GANs) are widely used to create photorealistic images [10-13]. However, in the case of applying such generative models to real physical data, the basic physical equations for the new examples generated by the model may not be satisfied. In this paper, we applied an approach to training the generative model for the reconstruction of turbulent flow fields [13]. The approach is based on the modification of the loss function, which is aimed at minimizing the residual part of the hydromechanics equations (continuity equation and the Poisson equation) for the generated data. This mathematical operation can significantly improve the properties of the model to reconstruct the physical dynamics of the turbulent flow. We applied and refined the algorithm for the turbulent flow of a submerged round jet. Accurate modeling of turbulent flow is extremely difficult due to the large number of degrees of freedom of a turbulent flow (proportional to $Re^{9/4}$). In [14], it was shown that GAN can demonstrate better results in the reconstruction of higher order moments.
than other popular machine learning approaches, such as the principal component method - in the literature on sections of hydromechanics better known as Proper Orthogonal Decomposition (POD). In a recent paper [15], neural networks that take into account the physical equations were developed to solve ordinary differential equations (ODE). In their solution, the authors used the root-mean-squared error function with the contribution not only of the solution error, but also with residual part of the differential equation. The approach was implemented and tested for a one-dimensional problem and cannot be extended for three-dimensional unsteady turbulent flows. In [12] generative models were used to create high-resolution photorealistic images. Despite the fact that the results are extremely encouraging, the approach cannot be applied to solving the current problem due to the absence of guarantees of physical realism of synthetic fields. In [14] generative models were used as an alternative to the well-known principal component analysis approach (PCA) to create complex geological models. It is shown that GAN reproduces the distribution of several physical quantities simultaneously.

This paper is devoted to the analysis of the applicability and creation of a generative adversarial neural network model, which allows learning from low spatial resolution data and reconstructing the relevant physical dynamics of the turbulent flow. This model can be used for many engineering applications. For example, for the reconstruction of low-dimensional modeling data, including for an approximate engineering calculation of the structural loads on a wind turbine, etc., the reconstruction of experimental data limited by the spatial resolution of the sensor. In this paper, we applied a generative adversarial neural network by analogy with [13] to reconstruct the structure and dynamics of a turbulent flow with an increased spatial resolution, which is important for analysis and interpretation.

The purposes of this work were to explore the possibilities of modern deep learning methods to study the structure and dynamics of complex turbulent flow.

2. Experimental and numerical database
The database of jet flow velocity fields was obtained as a result of 3D PIV experiment and DNS simulation. The non-swirling and swirling jet flows were organized in a closed hydrodynamic circuit, which included a water tank, pump, flowmeter, and test section. The rectangular test section (200×600×200 mm³) was made of Plexiglas (see figure 2). A contraction nozzle in the bottom of the test section produced the jet flow. The nozzle exit diameter d was 15 mm. A vane swirler was mounted inside the nozzle to organize jets with swirl. Details on the nozzle and mean velocity data can be found in [16]. The measurement volume of 40×40×40 mm³ (approximately 2.5d×2.5d×2.5d) was recorded by four high-speed CMOS cameras (Photron FASTCAM SA5). Polyamide seeding particles (50 μm in size) in the measurement volume were illuminated by a high-repetition pulsed Nd:YAG laser (Photonix DM100-532) with the average power of 100 W. The illumination area was organized as a vertical cylindrical beam of 40 mm in diameter. The in-house “ActualFlow” software, developed in the Institute of Thermophysics, was used to measure and process the acquired data. The acquisition frequency was 2 kHz. During each run 2000 images were recorded. Three independent runs were carried out for each swirl case to verify the consistency of the results for a single run. The separation between neighboring vectors was 0.84 mm. The spatial and temporal resolution was limited by approximately 3 mm and the 5 ms, respectively. Pressure fields were derived from velocity fields by solving the Poisson equation [16].

Direct numerical simulation data of a turbulent jet [17] performed with an in-house high-order finite-difference/pseudospectral code that solves the compressible Navier-Stokes equations using 400 million grid points. The computational domain was divided into subdomains to use a set of processor cores using MPI protocol and OpenMP. The computational grid used about 400 million nodes, which was sufficient to resolve even the smallest turbulent scales up to the size of Kolmogorov. We consider a jet at Reynolds number Re = 5940 based on the bulk velocity U_b in the pipe and its diameter D generated by a fully turbulent pipe flow entering a uniform stream with a coflow velocity \( u_{co} = 0.27U_b \). The physical region had a longitudinal coordinate along the flow up to \( x/D = 40 \). Together with a
sufficient spatial resolution, the computation features a very long-time realization with around 400$D/U_b$ time units, allowing one to statistically assess even the far field of the jet.

![Photographs of (a) experimental setup and (b) illuminated volume.](image)

**Figure 2.** Photographs of (a) experimental setup and (b) illuminated volume.

### 3. Flow fields reconstruction. Generative Adversarial Network

Three-dimensional PIV data on the velocity and pressure fields of dimension $12\times12\times12$ are fed to the input of the generative model. The model allows you to increase the frequency of spatial discretization up to $44\times44\times44$, while maintaining the physical properties of the generated distributions. The PIV database contained 2,500 velocity fields for 4 separate runs (10,000 total). Additional fields for training generative model were generated by using Reduced Order Model (ROM) based on POD technique [17]. Such an approach makes sense of augmentation, which is often used when training a neural network in order to increase the generalizing ability of a model. The full dataset contained about 15,000 velocity and pressure fields. Pressure fields were derived from velocity fields by solving the Poisson equation [16].

The generator is a ResNet residual network (residual neural network) architecture, each block of which includes convolutional layers with batch normalization. The discriminator is a deep convolutional neural network with fully-connected output layers for binary classification. The architecture of the generator and discriminator is shown in figure 3.
Figure 3. The architecture of generator and discriminator of generative adversarial neural network. In figure $k$ is the convolutional kernel size, $n$ is the number of channels, $s$ is the stride for each convolutional layer [13].

The velocity and pressure fields must satisfy the continuity equation and the Poisson equation: $\nabla u = 0$ and $\Delta p = -(u \nabla) u$, where $u = (u, v, w)$ is a three-component velocity vector, $p$ is pressure. However, these equations may not be exactly satisfied by the fields of the generative model. To overcome this drawback, the residual part of these equations can be used as a regularizer for the model. The total loss function of $Q_{\text{model}}$ includes 5 component terms:

$$Q_{\text{model}} = \alpha Q_{\text{resnet}} + (1 - \alpha) Q_{\text{adver}},$$

$$Q_{\text{resnet}} = \beta Q_{\text{field}} + (1 - \beta) Q_{\text{gove}},$$

$$Q_{\text{field}} = \gamma Q_{\text{MSE}} + (1 - \gamma) Q_{\text{enst}},$$

$$Q_{\text{gove}} = \delta Q_{\text{pois}} + (1 - \delta) Q_{\text{cont}}.$$

The loss function, which is minimized for the generator, is a linear combination of two loss functions $Q_{\text{field}}$ and $Q_{\text{gove}}$, which makes it possible to more accurately describe the physically relevant dynamics of the turbulent flow. $Q_{\text{field}}$: $Q_{\text{MSE}}$ is the standard deviation between the actual high-resolution velocity fields and the generated fields from GAN model. $Q_{\text{enst}}$ is the mean squared error in the resulting enstrophy $\Omega = \omega \omega$, where $\omega = \nabla \times u$ is the vorticity. $Q_{\text{gove}}$ is the residual part of the continuity and Poisson equations, considered by analogy with [13]. $Q_{\text{adver}}$ is the logistic loss function, defined by analogy with [13]. To train the discriminator, we used the logistic loss function for the classifier problem, which distinguishes between real and generated data examples. We used the generator model based on the residual neural network ResNet without the content part to check the convergence and tuning of the hyperparameters (the number of ResNet blocks and the parameters of the physical loss function $Q_{\text{gove}}$).

![Graph 1](image1.png)

**Figure 4.** Graphs of content ($Q_{\text{field}}$) and physical loss ($Q_{\text{gove}}$) functions depending on the number of iterations ($N_{\text{iter}}$) for different values of the coefficient $\beta$.

The used model of generative adversarial neural network includes a discriminator and a generator, shown in figure 3. The initial generator weights were initialized from the pre-trained ResNet model, the He-Xavier initialization was used for the discriminator weights. At the first ~ 100-300 iterations, only the discriminator is trained to compensate the advantage of the generator due to pre-selected weights. Then the discriminator and the generator were trained together in a competitive manner, until the loss functions come to a plateau, and the discriminator output reaches ~0.5 (see details in [13]). Adam (adaptive inertia optimizer) was used to update the weights and train both neural networks. The
size of the batch was 5 and was chosen to train both the ResNet model and the generative adversarial neural network due to the limitations of the available GPU memory. We chose the learning rate $\alpha = 0.0001$ in the process of optimization of the hyperparameters (iteration over the grid). In the process of learning, the coefficient for the physical and content parts of the loss function was analyzed. The coefficient $\beta = 0.9$ was selected based on a compromise between a decrease in the physical part and an increase in the content part of the loss function. To increase the sustainability of the generative model in the learning process, we reduced the speed of learning. The figure 4 shows the convergence curves of the loss function with increasing number of learning iterations for various values of $\beta$ coefficient.

Figure 5 shows a comparison of the velocity fields in the jet cross-section according to PIV data. For example, one cross-section $y/d=2.0$ of the jet is shown. Fields with a reduced resolution of $12 \times 12 \times 12$ were fed to the input of the generative model, while the original was about 4 times higher ($44 \times 44 \times 44$). In figure 5 it can be seen that the reconstructed image with good accuracy repeats the original velocity field in high resolution. This result was achieved by changing the loss function and adding the term responsible for the physical content.

4. Flow fields segmentation. Fully-Convolutional Neural Network

In this work, a fully-convolutional neural network (FCN) was used to solve the problem of segmentation of velocity vector fields of a turbulent jet. Similarly, each vector of three velocity components was considered by analogy with a separate RGB pixel in image segmentation. The deep learning model is based on the pre-trained neural network of the VGG-16, as was done in [5]. In our FCN implementation, we reuse the pre-trained VGG-16 layers numbered 3, 4, and 7, and then apply convolutions with the 1x1 filter to these layers. This stage resembles an encoder that extracts features from images. The encoding is followed by a decoding step using multiple layers of upsampling. Increasing the sampling rate occurs through the use of transposed convolution (inverse convolution operation). Figure 6 shows the structure of the encoder and decoder.

The network has been trained on using the following hyperparameters: learning rate = 0.0001, keep probability = 0.25, epochs = 25, batch size = 16, initial std = 0.01, number of classes = 2, image shape = $(64, 64)$. We used GAN model described below to increase the spatial resolution to $64 \times 64 \times 64$. Neural network weights optimization was performed by using Adam optimizer, and minization of cross-entropy loss function. The cross-entropy loss is computed against the correct ground truth image. Image labeling was performed on the basis of criteria for vorticity to determine the region of turbulent flow and axial velocity to determine recirculation zone.

For example, figure 7 shows the results of segmentation of instantaneous velocity fields of a swirling jet using a fully-convolutional neural network. For example, one cross-section $y/d = 1.0$ of swirling jet is shown. The green color shows the identified region of the turbulent flow of a swirling jet.
jet (with sufficient vorticity). The blue area in the center visualizes a segmented area of reversed flow. The gray area visualizes negative axial velocity values. You may notice that the segmentation area of the recirculation zone is slightly larger than the contour of the negative values of the axial velocity component. The figure shows a few typical situations. This is due to the fact that 3D velocity fields separated by slices are used when training fully-convolutional neural network. Extracting 3D flow structure information directly using 3D convolutions and increasing number of epochs during training process can improve segmentation accuracy. However, it is a fairly time-consuming in the computational point of view.

**Figure 6.** The architecture of fully-convolutional neural network (FCN) [6].

![Convolution network](image)

![Deconvolution network](image)

**Figure 7.** Examples of segmentation of instantaneous velocity fields of swirling jet in cross-section ($y/d = 1.0$) by using fully-convolutional neural network. The green contour shows region of turbulent flow, blue contour in the central part shows the segmented area of reverse flow, gray contour indicates negative values of the axial velocity in cross-section.

5. Conclusions

In this work, computer vision technology was tested on the basis of deep neural networks to solve problems of reconstruction of velocity and pressure fields of a turbulent flow with high resolution and to identify the characteristic flow features. In the process of research, two important tasks were considered. The first task concerned the construction of a model for the reconstruction of flow velocity fields with an increased spatial resolution, which is often important for the accompanying data analysis and modeling tasks. The second task was aimed at building a deep learning model for automatic detection of the characteristic turbulent flow features in instantaneous velocity fields. To solve these problems, an extensive databases of 3D PIV experiments and DNS modeling were used. To increase the dataset, an augmentation procedure based reduced order modeling was applied. It is shown that the generative adversarial neural network can be effectively used to increase the spatial resolution up to four times. The result was achieved by applying an approach based on modification of...
the loss function, which minimizes the residual part of the hydrodynamic equations (the continuity equations and the Poisson equation) for the reconstructed data. It is shown that generative models are more effective in the reconstruction of high moments of turbulent flow than conventional methods POD and DMD. The results show that the fully-convolutional neural network can be used for automatic segmentation of flow features, such as turbulent flow region, recirculation zone, coherent vortex structures, etc. This approach can be effectively applied to localize, determine the characteristic size and trajectory of vortex structures. The developed deep learning models can be effectively used to develop systems for automating the process of studying hydrodynamic flows.

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