Transfer learning for isolated cylinder vibration induced by vortex shedding

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Abstract. Transfer learning study on vortex-induced vibration of circular and bending cylinders in laminar flows. Vortex-induced vibrations of circular and bending cylinders have been detected by varying flow rate in rectangle cylinder. The vibration date in different position of the cylinders are acquired by LMS and image information obtained. The dynamic characteristics of vortex shedding are analyzed by the cylinder vibration and flow rate signal. The experimental data of the circular cylinder vibration is used as auxiliary data set and a few data of the bending cylinder vibration as target data set. Both of auxiliary and target data sets compose the training set which is trained by TrAdaboost based on weight iteration adjustment. The result compared with another experimental data of bending cylinder shows that the transfer learning algorithm has a reasonable accuracy.

1. Introduction

The flow-induced vibration of cylinder may cause the wear between cylinder and the supporting structure, which may lead to the damage of cylinder. Therefore, the flow-induced vibration of cylinder is of great research significance.

Sahu T R et al. [1] studied flow-induced vibration of a circular cylinder with an attached rigid splitter plate. Zhao J et al. [2] investigated the dynamic response of elastically-mounted elliptical cylinders with various cross-sectional aspect ratios in a free stream. Kim S et al. [3] identified the suppression characteristics and mechanisms of flow-induced vibration occurring in an experimental cylinder installed on an elastic support by placing a control cylinder.
with a smaller diameter behind the experimental cylinder. De Pauw B et al. [4] described an operational modal analysis (OMA) techniques to evaluate flow-induced vibration of nuclear reactor fuel pins subjected to a turbulent axial flow of heavy metal. Zhao W et al. [5] investigated dynamics of tubes subjected to cross flow. A fully coupled model for fluid dynamics and structure is used to analyze this fluid–structure problem. Bhattacharya A et al. [6] presented an experimental investigation of effects of angular misalignment on flow-induced vibration of two simulated 43-element CANDU fuel bundles in an out-reactor fresh water loop. Presented an experimental investigation of effects of angular misalignment on flow-induced vibration of two simulated 43-element CANDU fuel bundles in an out-reactor fresh water loop. Xu W H et al. [8] investigated streamwise flow-induced vibration of a circular cylinder with symmetric vortex shedding in the first instability range, and proposed a wake oscillator model for the dynamic response prediction. Carmom B S et al. [9] performed two- and three-dimensional numerical simulations of the flow around two circular cylinders in tandem arrangements. Assi G R D S et al. [10] showed new measurements on the dynamic response oscillations of an isolated cylinder and flow interference of two cylinders. Maruai N M et al. [11] conducted the computation of flow-induced vibration by numerical simulation based on the Unsteady Reynolds Navier-Stokes (URANS) flow field using OpenFOAM software.

Nowadays, machine learning is a hot topic in today's scientific research and is widely used in various fields. Traditional machine learning methods require training data and test data to meet certain assumptions about the same distribution, and need to obtain a large amount of known label data to build a model with good generalization performance. However, in addition to the lots of resources consumed by the flow-induced vibration experiment, it is very difficult to install the sensors in the experiment and some complex experimental environments to obtain enough useful and reliable experimental data.

In recent years, transfer learning, as an emerging learning method that uses the knowledge of the active domain to solve the problem of the target domain, has been widely used in the fields of natural language processing, computer vision, medical health, and fault diagnosis with its unique advantages. Zheng X et al. [12] proposed a new dictionary learning based on the hinge loss and SVM with multi-task transfer learning method(DMTTL). Qin C X et al. [13] presented transfer learning-based end-to-end speech recognition approach. Ahmad Z et al. [14] proposed an efficient technique to mitigate the problem of resource scarcity for emotion detection in Hindi by leveraging information from a resource-rich language like English. Kang Z et al. [15] made the first attempt to study online transfer learning with Multiple Source Domains for multi-class classification (MC), and proposed an algorithm, referred to as Online Multi-source Transfer Learning for Multi-class classification (OMTL-MC) algorithm. Yuan Y et al. [16] studied discriminative features for prostate images and assist physicians to classify prostate cancer automatically and developed a novel multi-parametric magnetic resonance transfer learning (MPTL) method to automatically stage prostate. Byra M et al. [17] proposed a neural network-based approach for nonalcoholic fatty liver disease assessment in ultrasound. Wu Z et al. [18] proposed an adaptive deep transfer learning method for bearing fault diagnosis. Mao W et al. [19] proposed a new online detection method of incipient fault based on deep transfer learning.

It is found that the vortex shedding phenomenon is related to the vibration amplitude of the experimental piece. From the data of piece that has been tested many times, we found that the
vortex shedding of the test piece was related to the flow rate and vibration amplitude. The data of tested pieces is used as auxiliary data, and a few data of test piece which we are going to test as the target data. Auxiliary and target data sets compose the training set of transfer learning. The experimental result shows that the transfer learning has a reasonable accuracy.

2. Theory

2.1. Vortex shedding

Vortex shedding is a periodic excitation with a linear relationship between frequency and fluid velocity, which is caused by the instability of free shear flow. It often occurs in the downstream of the structure affected by transverse flow, and there is a risk of wave in the downstream. The alternate vortex formed behind the structure will produce fluctuating lift and resistance. The vortex shedding frequency using dimensionless $S_r$ can be expressed as

$$S_r = f_s D/U$$

Where, $f_s$ is the main frequency of vortex shedding, $U$ is the velocity, $D$ is the diameter of the cylinder.

Through a lot of experiments and theoretical studies, it is shown that $R_e$ is the main parameter to determine the flow pattern. When $R_e < 5$, the flow will not separate; when $5 < R_e < 3 \times 10^4$, it is a stable vortex flow, that is a pair of stable vortices with fixed positions appear behind the cylinder. With the increase of $R_e$, the energy brought by the peripheral fluid to the vortices increases, and the vortices also increase, and then the vortices begin to swing left and right downstream of the cylinder. When $R_e < 40$, the vibration is stable. When $R_e > 40$, the vibration is unstable. After a certain period of time, one vortex begins to fall off behind the cylinder. After a certain period of time, another vortex will fall off. After the vortex falls off, a new vortex will be generated behind the cylinder. When the vortex develops to a certain strength, the new vortex begins to fall off again, and two rows of interleaved vortices will gradually form downstream of the cylinder. This is Carmen vortex street. In case of $R_e < 150$, the vortex street state is laminar flow. In case of $150 < R_e < 300$, the vortex changes from layer to turbulence. In case of $300 < R_e < 3 \times 10^5$, the boundary layer on the cylinder surface is laminar flow, while the vortex street behind the cylinder has completely changed to turbulent state, and the vortex is released at a certain frequency, which is called subcritical region. In case of $3 \times 10^5 < R_e < 3 \times 10^6$, The boundary layer on the surface of the cylinder has also turned into turbulence. The resistance has dropped significantly. The wake flow shows randomness, and there is no obvious vortex. This is called the critical zone. When $R_e > 3 \times 10^6$, this is supercritical zone with a regeneration of relatively regular quasi-periodic vortex street.

2.2. Transfer learning

The phenomenon of transfer learning exists in various fields of real life. Many simple examples of daily life can also explain the rationale of transfer. For example, people who learn to ride bicycles can easily learn to ride motorcycles. People who learn English are more likely to learn Spanish. The basic idea of transfer learning is to learn the basic knowledge within a known source domain (auxiliary domain) and apply the learned knowledge to different but related unknown domains (target domains) to solve similar problems.
The TrAdaboost transfer learning algorithm is a machine learning algorithm based on weight iterative adjustment. The learning process of the transfer learning algorithm TrAdaboost is as follows:

The auxiliary data and the target data constitute training data, and the data weight vector in the training data is first initialized (the first generation weight vector is set):

\[ w^1 = (\omega_1^1, \cdots, \omega_{n+m}^1) \]  
\[ \omega_i^1 = \begin{cases} 1/n, & i = 1, \ldots, n \\ 1/m, & i = n+1, \ldots, n+m \end{cases} \]  

Where \( n \) is the sizes of auxiliary data, and \( m \) is the sizes of target data.

Set the weight distribution \( p^t \) to satisfy:

\[ p^t = \sum_{i=1}^{n+m} \omega_i^t \]  

Where \( t \) is the maximum number of iterations.

Based on the training data set and its weight distribution, a classifier is obtained \( h_t \), and the error of \( h_t \) on target data set is calculated:

\[ e_t = \sum_{i=n+1}^{n+m} \omega_i^t |h_t(x_i) - c(x_i)| \]  

Where \( c(x) \) is the real label of data.

Setting parameters:

\[ \beta_t = e_t / (1 - e_t) \]  
\[ \beta = 1 / (1 + \sqrt{2 \ln n/N}) \]  

Update the weight vector of next iteration:

\[ \omega_i^{t+1} = \begin{cases} \omega_i^t \beta_i^{h_i(x_i) - c(x_i)}, & i = 1, \ldots, n \\ \omega_i^t \beta_i^{h_i(x_i) - c(x_i)}, & i = n+1, \ldots, n+m \end{cases} \]  

After all iterations, the output of final model is obtained:

\[ h(x) = \begin{cases} 1, & \prod_{i=N/2}^{N} \beta_i^{h_i(x)} \geq \prod_{i=N/2}^{N} \beta_i^{1/2} \frac{1}{2} \\ 0, & \text{otherwise} \end{cases} \]  

It can be seen that in each iteration of the round, if an auxiliary training data is misclassified, then we can reduce the weight of this data. Specifically, it is to multiply the data by \( \beta_i^{h_i(x) - c(x_i)} \), where the value \( \beta \) is between 0 and 1, so in the next iteration, the misclassified sample will have less impact on the classification model than the previous round. After the iteration, the data in the auxiliary data that meets the target data will have a larger weight, and the weight of auxiliary data that do not meet the target data will gradually decrease. After the iteration is completed, the classification model is finally generated.
3. Experiment

3.1. Experimental loop
The main performance parameters of the experimental device are as follows: the rated flow of the single loop circulating main pump is 1450 m$^3$/h. The lift is 80 H$_2$O. The working medium is deionized water. The maximum working pressure can reach 1.3 MPa. The working temperature $\leq 90$ ℃. The volume of the pressurizer is 2.4 m$^3$. The experimental flow is 200m$^3$/h~700m$^3$/h. The power of the heat exchanger is 620kW. The loop flow is measured with LW-300 turbine flowmeter during operation, and the error is 1%. The loop flow diagram of the experimental device is shown in the figure below.

![Loop flow diagram](image)

Figure 1. Loop flow diagram
1. Water tank 2. Supply pump 3. Circulating water pump 4. Flowmeter 5 Experimental section

The equipment, valves and cylinders in the circulation loop system of the experimental device are made of stainless steel. The circulation process of each main circuit is as follows: the deionized water from the main pump is divided into pump bypass and experimental bypass. The experimental bypass enters the simulation body of the experimental piece after the flow is measured by the flowmeter. The fluid from the simulation body mixes with the fluid from the pump bypass, and returns to the main pump to form a closed fluid circulation flow.

3.2. Experimental ontology
The flow induced vibration experimental piece of spiral heat transfer cylinder bundle includes a single circular cylinder and a single bending cylinder. The single cylinder flow induced vibration experiment body is mainly composed of an inlet section, an inlet stable section, an experimental section, an outlet stable section, and a experimental piece. The experiment body is placed horizontally to ensure that the experimental piece is placed vertically. The deionized
water medium flows in from the inlet section and flows out from the outlet section.

a) The net length of the circular cylinder of the experimental piece of a single circular cylinder circular cylinder flow induced vibration experiment is 550mm, outer diameter is 20 mm and thickness is 2.5mm. One end of the cylinder is fixed on the wall surface by welding and expanding, and the other end is free. The distance between the outer surface of the cylinder and the wall surface of both sides of the flow passage is 45mm, and the distance between the free end of the cylinder and the wall surface of the inner flow passage is 11mm.

b) The net arc length of the bending cylinder of the experimental piece for the flow-induced vibration experiment of a single bending cylinder is 550mm the outer diameter and thickness are Φ 20 × 2.5mm. The fixed end of the cylinder is welded with a circular section of cylinder at the lower end of the bend. The length of the circular cylinder is consistent with the thickness of the fixed plate, and then fixed on the fixed plate by welding and expansion. The distance between the center of the bend and the wall surface of the flow passage at both sides is always 45mm, and the distance between the cantilever end of the cylinder and the wall surface of the flow passage is 11 mm.

3.3. Arrangement of measuring points
The sensors used in this experiment include: 8 triaxial acceleration sensors, LMS data acquisition system, measurement and control system, etc. The range of acceleration sensor used in the experiment is ± 522g, and the frequency response range is 2-4Hz.

In order to measure the vibration response of cylinders under different flow rates, an acceleration sensor is arranged in the middle and the end of each circular cylinder and bending cylinder to measure the vibration of cylinders. The acceleration sensor is installed inside the experimental cylinder, and a screw hole with a diameter of 3mm is opened on the wall of the experimental cylinder. The sensor is installed on its auxiliary device, and then the experimental cylinder is screwed connect with the sensor installation auxiliary device. The acceleration sensor line runs directly from the inside of the experimental cylinder, and the outgoing line from the hole of experimental cylinder is connected with the measuring system.

4. Result
4.1. Result of step flow experiment of circular cylinder
In the step flow experiment of circular cylinder, the flow rate starts from 100 m³/h, and one steady state experiment is performed for each increase of about 30 m³/h until the flow rate reaches 600 m³/h, and the vibration response of the cylinder under each steady state condition is measured. In this experiment, 17 groups of experimental data of step flow condition of circular cylinder are obtained, and the curve of acceleration vibration amplitude with flow rate can be obtained by processing each group of experimental data. Figure 2 is the curve of the maximum acceleration of the circular cylinder with the flow rate.
According to the curve of acceleration with flow rate in the figure, it can be preliminarily determined that the flow rate of vortex shedding is 478.1 m$^3$/h. In order to verify whether the flow rate is the starting point of vortex shedding, the spectrum curve of acceleration signal is obtained through the post-processing of experimental data. Figure 3 and Figure 4 are the acceleration spectrum curves of circular cylinder at flow rates of 446.3 m$^3$/h and 478.1 m$^3$/h. As can be seen from the spectrum, there is no vortex shedding at flow rate of 446.3 m$^3$/h. It can be concluded that the circular cylinder begins to vortex shedding when the flow rate is 478.1 m$^3$/h and the frequency of vortex shedding is about 23.67Hz.

4.2. Result of step flow experiment of bending cylinder
In the step flow experiment of bending cylinder, the flow rate starts from 100 m$^3$/h, and one steady state experiment is performed for each increase of about 30 m$^3$/h until the flow rate reaches 700 m$^3$/h, and the vibration response of the cylinder under each steady state condition is measured. In this experiment, 20 groups of experimental data of step flow condition of bending cylinder are obtained, and the curve of acceleration vibration amplitude with flow
rate can be obtained by processing each group of experimental data. Figure 5 is the curve of the maximum acceleration of the bending cylinder with the flow rate.

![Graph of maximum acceleration vs. flow rate](image)

**Figure 5.** Curve of the maximum acceleration of the bending cylinder with the flow rate

According to the curve of acceleration with flow rate in the figure, it can be preliminarily judged that the flow rate of vortex shedding is 539 m$^3$/h. In order to verify whether the flow rate is the starting point of vortex shedding, the spectrum curve of acceleration signal is obtained through the post-processing of experimental data. Figure 6 and Figure 7 are acceleration spectrum curves of bending cylinder at flow rates of 508 m$^3$/h and 539 m$^3$/h. As can be seen from the spectrum, there is no vortex shedding at flow rate of 508 m$^3$/h. It can be concluded that the bending cylinder begins to vortex shedding when the flow rate is 539 m$^3$/h flow rate and the frequency of vortex shedding is about 27.53 Hz.

![Acceleration spectrum curve at 508 m$^3$/h](image)

**Figure 6.** Acceleration spectrum curve of bending cylinder at flow rate of 508 m$^3$/h

![Acceleration spectrum curve at 539 m$^3$/h](image)

**Figure 7.** Acceleration spectrum curve of bending cylinder at flow rate of 539 m$^3$/h

### 5. Discussion

The vibration image and video of the cylinder recorded by the high-speed camera is used to obtain the curve of the maximum vibration amplitude. Combined with the corresponding acceleration and flow rate data above, the positions of the two obvious starting points of
vortex shedding are also obtained as shown in the figures below.

**Figure 8.** Curve of maximum vibration amplitude of circular cylinder with flow rate

**Figure 9.** Curve of maximum vibration amplitude of bending cylinder with flow rate

This method only uses the flow rate and the amplitude data obtained from the image for transfer learning. The experimental data of the circular cylinder is used as auxiliary data set and a few data of the bending cylinder vibration as target data set. Both of auxiliary and target data sets compose the training set of TrAdaboost, and the results are compared when the number of target data is different.

| Number of target data | Flow rate at the starting point of vortex shedding |
|-----------------------|-----------------------------------------------|
| 2                     | 508                                           |
| 3                     | 508                                           |
| 4                     | 539                                           |
| 5                     | 539                                           |

It can be seen from the table that in the case of a small amount of target data, the flow rate of vortex shedding point can be obtained by accurate training and learning, but when the number of target data is barely, the accuracy of the learning results is not very satisfactory. Therefore, transfer learning still has some requirements for the quantity and representativeness of the target data. If the number of target data is scarce, the algorithm will rely heavily on auxiliary data for training and learning, which will affect the accuracy of transfer learning. But in the case of small amount of target data, the result of transfer learning is extremely accurate.

**6. Conclusion**

In this paper, the acceleration and image data of circular cylinders and bending cylinders under different flow rates are collected in vortex-induced vibration experiment, and the
frequency of vortex shedding and the flow rate of vortex shedding are determined by analyzing the spectrum. The amplitude and flow rate in the collected images of circular cylinder and bending cylinder as the training data of transfer learning. The data of circular cylinder is used as auxiliary and a small amount of data of bending cylinder is used as the target data. Both of auxiliary and target data sets compose the training set which is trained by TrAdaboost based on weight iteration adjustment. The result shows that this method can allow us to learn an accurate model using only a small amount of target data. With the help of transfer learning model, we do not need to equip lots of sensors in the experimental body. We just need to use a high-speed camera to capture images of cylinders, and then we can judge whether the vortex is shedding in the experiment.

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