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Oil-in-Water Two-Phase Flow Pattern Identification From Experimental Snapshots Using Convolutional Neural Network

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ABSTRACT The flow pattern is one of the most significant parameters in modeling the oil–water two-phase system. How to extract efficient and objective features to precisely identify the oil–water two-phase flow patterns is still a significant issue. Inspired by the deep learning hierarchically feature extraction way, we, in this paper, employ convolutional neural networks (CNNs) to identify oil–water two-phase flow patterns. First, we carry out oil–water two-phase flow experiment and collect different oil–water flow pattern images. Then, we propose an image segment algorithm based on the minimum gray level to obtain the interest region that reflects the flow pattern characteristics. Finally, we employ three frequently used CNNs, LeNet-5, AlexNet, and VGG-16 net, to extract the image features and identify typical oil–water two-phase flow patterns. The results show that networks with more deep structures preserve relatively high flow pattern recognition accuracy. This paper provides a novel application of the deep learning method for the oil–water two-phase flow identification.

INDEX TERMS Fluid flow, image classification, machine learning, neural networks.

I. INTRODUCTION

Oil-water two-phase flow widely exists in petroleum industry such as crude oil production and transportation. As a key parameter, the flow pattern plays a very significant role in modeling oil-water two-phase flow system. Correctly recognition of flow patterns is of great importance to the oil-water two-phase control system design and monitoring. Moreover, the pressure drop prediction of pipe system is quite related the flow pattern evolutional phenomena. Therefore, correctly recognize the complex oil-water two-phase flow patterns became a challenge problem of significant importance. Early studies of oil-water two-phase flow patterns identifications mainly focus on experimental observations [1]. Mini-probe detection [2] is the most commonly used method for oil-water flow pattern identification. Other methods such as process tomography [3] high-speed camera observation [4] and PIV technology [5] also have been adopted for flow pattern investigation.

Recently, much researchers focus on indirect methods to identify oil-water two-phase flow patterns. These methods extract and fusion flow pattern dynamic features from experimental fluctuation signals and identify different flow patterns. The fluctuation signals used for identification are time series that collected to reflect the conductance or pressure fluctuations of the mixed fluid. Note that different flow pattern features represent different aspects of fluid physical dynamics. For example, time-frequency features [6] reveal motion behaviors of flow pattern, wavelet [7] and Hilbert-Huang transform [8] features mainly reflect the flow pattern multi-scale dynamics character, nonlinear features [9] is advanced characterizing flow pattern evolution dynamics. It is worth noticing that complex network features [10], [11] have recently been proved to be effective criteria for flow pattern identification. Generally speaking, the flow pattern identification methods based on fluctuation features are less affected by flow conditions such as pipe direction and diameter. In this regard, this method provides an effective solution for flow pattern identification.

Another powerful tool used for flow pattern identification that attracts many researchers is the machine learning technique. Useful information or characters are extracted to train a network which represents the relationship between the measured data and the patterns to be identified. The most common used machine learning method to recognize flow patterns is the artificial neural network (ANN). To obtain effective recognition and prediction results, researchers try to employ different kind topology such as Feed Forward Neural Networks [12] self-organizing neural network [13], Multiple Layer Perceptron [14], et. al. to construct the recognition network. In addition, support vector machine (SVM) which is proposed by Cortes and Vapnik [15] in 1995 is also frequently used to solve the two-phase flow parameter prediction [16] and pattern identification [17] problems. Since it is independent of any specific model and does not have the local minimization problem, the SVM model shows excellent flow pattern identification results. The machine learning methods can be considered as effective tool for flow pattern modeling and identification. However, these methods are quite related to the collected data or the extracted features. In this regard, elaborately designing the training data set is the key factor to improve the flow pattern identification accuracy.

How to get effective features that represent the flow pattern characteristic is the key point for two-phase flow pattern identification. Features that extracted from experimental fluctuation signals can only represent one side of flow character. It often needs to fusion several features to finish the identification task. While the machine learning features that used for model training are often designed subjectively and quite rely on the data set. Hence, developing a reliable and objective feature extraction method for two-phase flow pattern identification became necessary. Quite recently, the deep learning theory [18] provides a new view for the feature representation. With a considerable deep structure network and hierarchically feature abstraction strategy, the high-level features can be considered as objective and reliable representations. Now the deep learning theory has been successfully applied in the field of image recognition [19], face recognition [20], speech recognition [21], denoising [22], biological data mining [23], estimating and prediction problem [24], [25], time-series modeling and classification [26] et al. It is worth noticing that some researchers attempted to employ deep learning method to investigate fluid flow problems. Ma *et al.* [27] use long-short-term memory (LSTM) networks to exploit the hidden patterns in fluid acoustic time series to predict the RMS acoustic power which is related to the density changes in the fluid flow. They found that LSTM is a more efficient predictor than neural network. Han *et al.* [28] train hierarchical recurrent network to characterize the response of micro-fluid soft sensor. The results show that both the nonlinear responses and contact locations can be estimate with this proposed network. Ling *et al.* [29] employ DNN model established an improved representation of Reynolds stress anisotropy tensor with simulated data. Chang and Dinh [30] adopt deep learning strategy to construct five machine learning frameworks for thermal fluid simulation. Lore *et al.* [31] employ deep learning strategy to learn the complex flow patterns in micro-channels and study the inverse problems in fluid mechanics. Ezzatabadipour *et al.* [32] employ multilayer perceptron with many hidden layers to predict the two-phase flow patterns. The experimental results show that flow condition such as pipe characteristics, fluid properties and superficial velocities can be used to predict the flow patterns. Poletaev *et al.* [33] studied a number of different neural network structures and choose convolutional neural networks to identify the bubble images and the proposed network is able to determine overlapping, blurred, and non-spherical bubble images.

Although much progress have been achieved in the field of flow pattern modeling and identification, it is still need to explore new flow pattern feature representations which could be improve the flow pattern identify accuracy. Inspired by the hierarchically feature abstraction strategy, we in this paper use deep learning theory to objectively extract the flow pattern features. As we know, the recently posted deep learning based flow pattern researches are all focus on gas-liquid system, there is no similar reports that associated with oil-water two-phase system. We in this paper carried out oil-water two-phase flow pattern test in a vertical 20mm inner-diameter pipe, and collected different flow pattern images that contain rich flow pattern evolution dynamic characteristics. Considering the excellent performance of convolutional neural network (CNN) in image recognition, we employ three frequently used CNN structures to identify the oil-water two-phase flow patterns. The remainder of this paper is organized as follows. In Section 2, we introduce the oil-water two-phase flow experiment and the collected images. A minimum gray-level based method is proposed to segment the original collected images and obtain the region of interest (ROI) which is used for the flow pattern recognition network training. In Section 3, we discuss several different CNN topologies which could be applied to identify the flow pattern images. In Section 4, we compare and discuss the recognition results of the proposed network. And finally we conclude this study in Section 5.

II. EXPERIMENTS AND ROI EXTRACTION

A. EXPERIMENTAL FACILITY AND PROCEDURE

We carried out oil-in-water two-phase flow experiment in a vertical 20mm inner diameter Plexiglas pipe to collect different flow pattern images. As shown in Fig.1 the flow loop experiment facility consist of two peristaltic metering pumps, a water tank, an oil tank, a mix tank and testing pipes. During the experiment, oil and water are pumped out from oil and water tanks respectively and mixed with a T-junction. Then the mixed fluid flow into an 1800mm length horizontal pipe. The vertical testing pipe and the horizontal pipe are connected with a 20mm inner diameter elbow. In order to fully develop the oil-water two-phase flow patterns, the vertical pipe is set as 1500mm long. The high speed camera and LED backlight are fixed at top of the testing pipe. After the flow pattern images are collected by the camera, the mixed fluid is drained into the mix tank to separate. The experiment mediums we used here are tap water and industry white oil which is

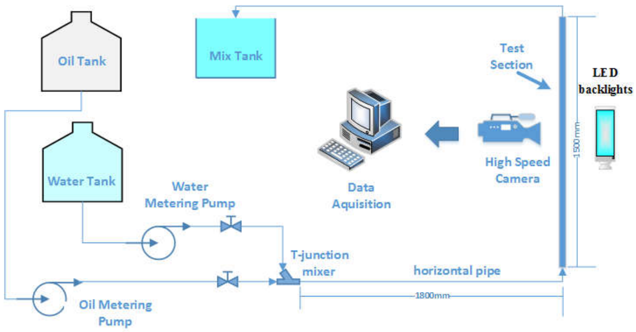

FIGURE 1. Schematic of oil-water flow loop facility.

dyed red. Peristaltic metering pumps are calibrated to ensure the accuracy of the inlet flow rate.

The image capture system contains a high speed camera, a LED backlights and computer. The resolution of the camera is set as 960×720. The LED backlight provides enough lighting to guarantee clearly images. The experimental schedule is as follows: we first fix the value of water phase fraction and then gradually increase the total velocity of mixed fluid. At the certain preset total flow rate, we collected the oil-water two-phase flow pattern images and store these images into computer. In the experiment, the water phase fraction is in the range of 70%-100%, while the mixture total flow rate was set at 0.01842 m/s, 0.03684 m/s, 0.07368 m/s, 0.11052 m/s, 0.14737 m/s, 0.18421 m/s, and 0.22105 m/s, respectively.

During the experiment, we observed three typical oil-in-water two-phase flow patterns, that is oil slug flow, oil bubble flow, and the very fine dispersed oil bubble flow (VFD bubble flow). As shown in Fig.2 (a), oil slug flow occurs in very low mixture velocity. In such flow condition, the dispersed oil droplets coalesce into slugs which intermittently pass though the vertical testing pipe. With increasing the mixture velocity, the flow pattern changes to oil bubble flow. Fig.2 (b) exhibit typical pattern of oil bubbles, which is distributed in the continuous water phase in the form of discrete droplets. With even more increasing of the total mixture velocity, as shown in Fig.2 (c) the discrete oil bubbles change to very small oil droplets that are uniformly distributed in the continuous water phase which is known as VFD bubble flow.

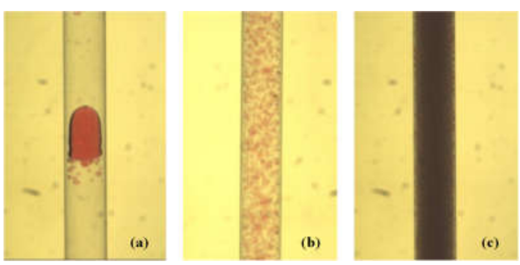

FIGURE 2. Images of three typical flow patterns. (a) Oil-slug flow. (b) Oil bubble flow. (c) VFD oil bubble flow.

B. FLOW PATTERN ROI EXTRACTION

As shown in Fig.2 the flow pattern images collected contain large redundant information, so we need to extract the region of interest (ROI) that can precisely reflect the flow pattern

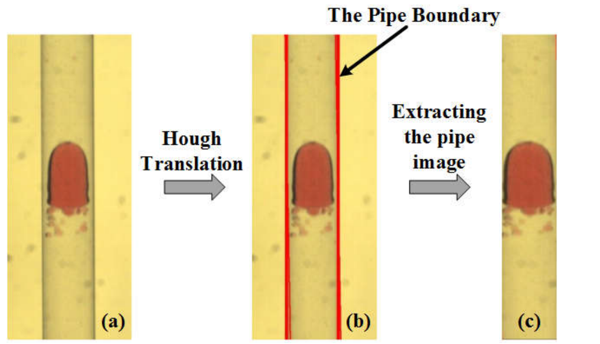

FIGURE 3. Pipe borders location of the original flow pattern image.

characters. As shown in Fig.3 (a) the original flow pattern image consist of background, the Plexiglas pipe and the oil-water mixture in the pipe. When training the identification model, we only concern about the mixed fluid in the pipe. In this regard, we need to segment the flow pattern target in the testing pipe.

Considering that lines are typical characteristics of the pipe in the original collected images. We employ Hough transform method [34] to make a segmentation to obtain the oil-water mixture images in the pipe. As shown in Fig.3 (b) after the Hough transformation, the border of the pipe has been detected. So we can locate the oil-water two phase flow image in the pipe.

It is worth to note that oil-slug flow exhibit intermittent character. Under this flow condition, oil slugs sparsely pass through the pipe and most part of the pipe is filled with water. So we need to make further segmentation that only keeping the oil slug part. Here we propose a segmentation method based on minimum gray level. We define a rectangle with the same width as the segmented pipe borders and the length of the rectangle is set as 30mm. According to experiment observation, oil slug in 20mm inner diameter pipes is no longer than 30mm. So, a complete oil slug can be included in this rectangle. Then we change the entire pipe images to grayscale and search the pipe with the preset rectangle from top to the bottom. As shown in Fig.4, we calculate the summation of the gray scale value in the rectangle, and then we can locate the oil slug with the minimum gray scale value. The size of testing pipe image is 720×200 pixels, and we set the searching step as 1 pixel. Because the pixels are the basic elements of the collected images, 1 pixel is the highest precision we can achieve. In this regard, we have chosen 1 pixel as the searching step. Note that oil bubble flow and very fine dispersed oil bubble flow are typical homogeneous flow pattern, small oil droplet uniformly distributed in the continuous water phase. So we segment the pipe images use the same size of rectangle, which can include all the information of oil bubble flow and VFD bubble flow.

III. METHODS

Traditional flow pattern identification methods are based on extracted fluctuation features which could characterize

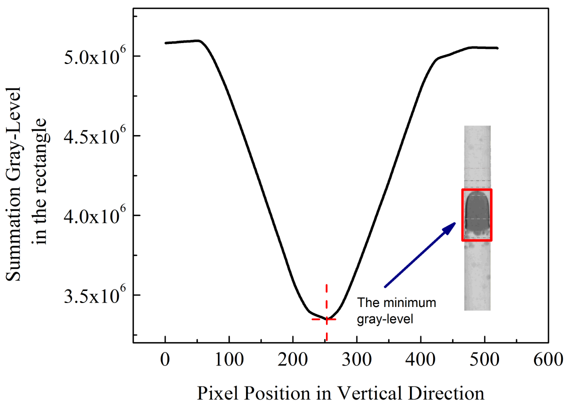

FIGURE 4. The gray-level summation in the rectangle along with the pipe axial direction.

the system dynamics. These methods are reflective and less affected by flow conditions. However, the extracted features can only reflect one side of the flow pattern characters and it often need to elaborately designed. Sometimes it often leads to misidentification when the flow pattern transition occurs even with fusion several features. However, under the deep learning strategy, features are hierarchically extracted by the deep network that the deep learning features can be regard as more objectively representations. So, we in this paper employ the deep learning strategy to recognize the oil-water two-phase flow patterns.

Among different deep learning structures, the convolutional neural network (CNN) has achieved vast success in the image identification [35]–[38]. We in this paper choose three frequently used CNN which are LeNet-5, AlexNet, and VGG-16 net to train the oil-water flow pattern identification network. These three CNN structures have difference network depth and filter size. With this research we try to find out the impact of the network parameters such as depth and filter size on the flow pattern recognition accuracy. In section IV where recognition results are discussed and the recognition accuracy for all flow patterns have reached a relatively high level with using VGG-16 net. So, other CNN structures with very deep structures such as GoogLeNet are not considered in this paper.

A. LeNet-5

LeNet-5 [39] is a typical convolutional Neural Network that initially used to identify handwriting pictures. As shown in Fig.5 it contains 3 convolution layers, of which the first two convolution layers are followed by pooling layer. The first convolution layer employs 6 filters of the size 5×5 to extract feature map and the following pooling layer reduce the feature map to the size of 14×14×6. The second convolution layer use 16 filters with the size 5×5, and the followed pooling layer reduce the feature map to the size of 5×5×16. The 3rd convolution layer connected to a fully-connected layer with 120 nodes and the last layer of LeNet-5 is softmax layer with 10 outputs. Considering that there are only three oil-water flow patterns to be identified, we modify the softmax output to 3.

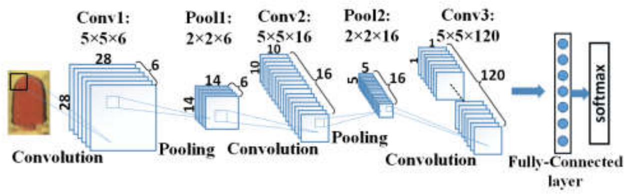

FIGURE 5. The architecture of LeNet (LeCun *et al.* [39]).

B. AlexNet

As a special designed convolutional neural network, the AlexNet proposed by Krizhevsky *et al.* [40] in 2012 exhibit quite excellent image recognition results and won the Large-Scale Visual Recognition Challenge (ILSCRC) in 2012 with an error rate of approximately 16.4%. As shown in Fig.6, the AlexNet consists of 5 convolution layers, 3 max pooling layers and 3 fully connected layers. In the first convolution layer, 48 filters with the size of 11×11 are applied to the original input images to extract features. Totally 48 feature maps are extracted and then followed by max polling layer. In max pooling layer the convolution features are reduced by keeping the maximum value of the extracted feature map to improve the feature representation. The second convolution layer uses the same structure as the first convolution layer but with different filter size and number. There is no max-pooling operation in the 3rd and 4th convolution layer. And the last convolution layer employs 128 filters with dimension 3×3 to obtain the feature map and also be applied with the max-pooling operation. The 6th and 7th layers are fully-connected network which contain 2048 neurons respectively and the last layers of AlexNet is the softmax with 1000 output. In the AlexNet model Rectified Linear Unit (ReLU) function is used as the activation function that applied to all the convolution layers and fully-connected layers. Also, we modify the softmax output from 1000 to 3 to meet the need of flow pattern identification task.

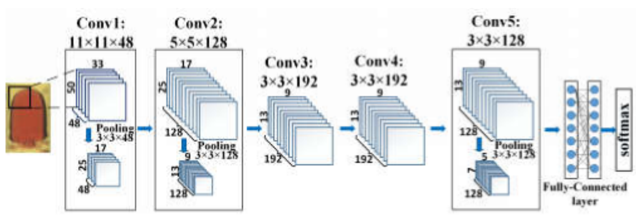

FIGURE 6. The architecture of AlexNet (Krizhevsky *et al.* [40]).

C. VGG-16 NET

In this paper, we also adopt the VGG-16 net [41] to recognize the oil-water two-phase flow patterns. Compared to the architecture of AlexNet, it has more convolution and max-pooling layers and the filter used in this network are smaller than

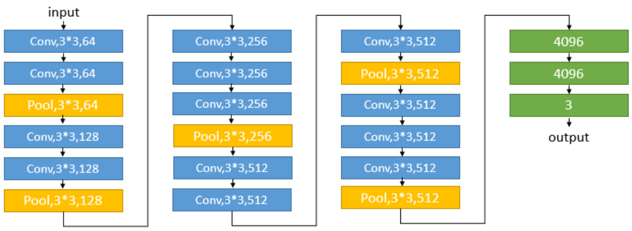

FIGURE 7. The architecture of VGG-16 net (Simonyan *et al.* [41]).

that used in AlexNet. As shown in Fig.7, the VGG-16 net contains 13 convolution layers and 5 max-pooling layers. The dimension of convolutional filter used in this network is 3×3 which is smaller than that of AlexNet. Small convolution filters will extract more local features of the input images and reduce the network parameters. Similar to the AlexNet, the last three layer of VGG-16 net are fully-connected layer and the softmax layer. Also, in order to meet the need of flow pattern number, the softmax output is redefined to 3.

IV. RESULTS AND DISCUSSION

By applying the flow pattern segment arithmetic that is proposed in section 2 to the experimental collected oil-water flow pattern images, we select totally 23900 flow pattern images to train and test the flow pattern recognition network. The training set consist 23000 images in which there are 2000 oil-slug flow images, 13000 oil-bubble flow image, and 8000 VFD oil-bubble flow images. The rest of the images are used as test data set, which contain 300 slug flow images, 300 oil-bubble flow images and 300 VFD oil-bubble flow images. Fig.8 shows the typical segmented flow pattern images.

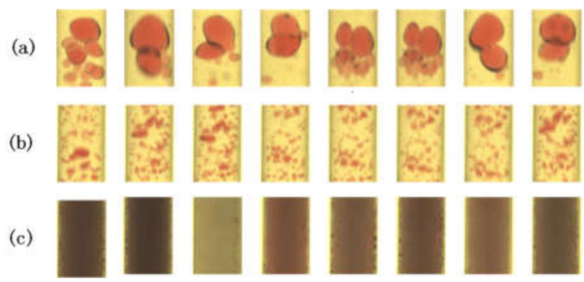

FIGURE 8. Segmented flow pattern representations of each flow pattern. (a) oil-slug flow, (b) oil-bubble flow (c) VFD oil-bubble flow.

LeNet-5, AlexNet and VGG-16 net have been trained to construct the oil-water two-phase flow identifier. When training these networks, we use the same input image size, Batch size and Learning rate where the input size is set as 130×200, the Batch size is set as 100 and the Learning rate is set as 0.00001. The dropout rate for AlexNet and VGG-16 net is set as 0.5, and there is no dropout operation when training the LeNet-5.

Fig.9 shows the loss value and the training accuracy of the three flow pattern identifier. We find that with increasing the iteration number the loss values of the three networks

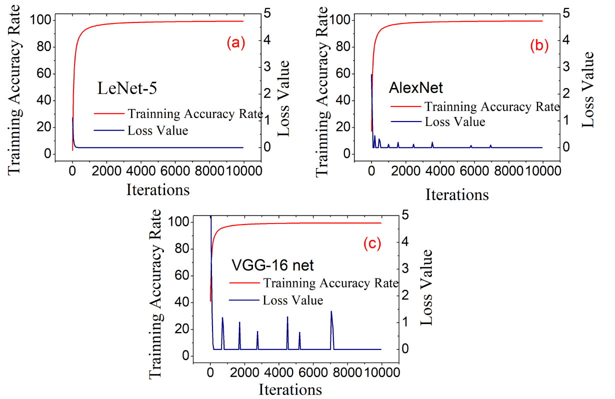

FIGURE 9. The training process of oil-water flow pattern identification networks. (a) LeNet-5. (b) AlexNet. (c) VGG-16 net.

gradually decrease to nearly zero which proves that these networks have converged. Also, we obtain the network training accuracy every 50 iterations, and the accuracy reaches nearly about 100% with increasing the iterations showing that the networks have been well trained.

After the three typical flow pattern identification networks have been well trained. We use the test data to evaluate the proposed three network structure. As shown in Fig.10 we compared the flow pattern identification results of the three CNN. Oil-slug flow images contain obvious morphology and interface features, which can be easily extracted by the convolution filter, hence the oil-slug flow recognition accuracy show relatively high value for all the three networks. The oil-bubble flow images exhibit small oil-drops uniformly dispersed in the water phase and the bubble interface morphology is the main character of this flow pattern. The LeNet-5 with less filters and layers which is insufficient in extracting the oil bubble local interface features. In this regard, the oil-bubble flow identification accuracy of LeNet-5 (88.0%) is lower than that of AlexNet (99.3%) and VGG-16 net (98.3%). VFD oil-bubble flow occurred at relatively high mix velocity and the oil-phase is breaking into very small and fine dispersed oil droplets. From the images of VFD oil bubble

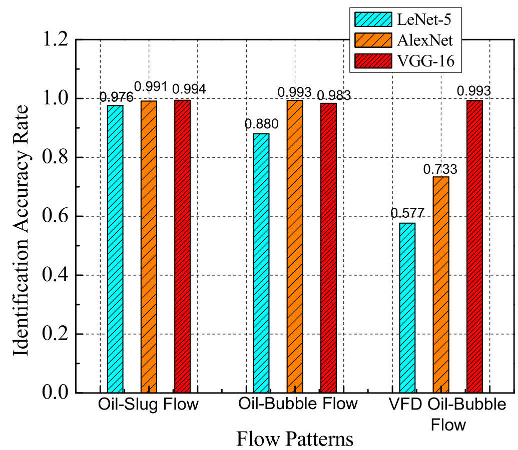

FIGURE 10. The flow pattern identification results of LeNet-5, AlexNet and VGG-16 net.

flow, no obvious interface character can be found. Deeper networks with smaller filters such as VGG-16 net can precisely extract the VFD bubble flow local features which can reflect the flow pattern character, hence the VGG-16 net preserve a relatively high identify accuracy (99.3%) for VFD oil-bubble flow. Compared to VGG-16 net, the AlexNet with larger filters and fewer layers may more sensitive to the flow pattern global features. So the VFD oil-bubble recognition accuracy of AlexNet (73.3%) is lower than that of VGG-16 net. Compared to the other two networks, the LeNet-5 which has fewest layers may only sensitive to flow pattern global interface characters, resulting low identification accuracy (57.7%) for VFD oil-bubble flow. Generally speaking, all the three networks can effectively recognize flow patterns that rich in obvious global morphology features, i.e., oil-slug flow. While for VFD bubble flow which has no obvious morphology character, it needs to employ networks with more layers.

Oil-water two-phase flow pattern is related the flow conditions such as flow rate, phase volume fraction, pipe diameter, inclination, etc. In other words, when the flow condition is fixed the flow pattern will not change. In the industrial applications, flow pattern identification task is often conducted under certain fixed flow condition. A series of flow images or signals is collected which only reflect the flow pattern under this flow condition. The proposed CNN based flow pattern identification network already has relatively high accuracy. Take VGG-16 net as example. The flow pattern recognition accuracy is 99.4%, 98.3% and 99.3% for oil-slug flow, oil-bubble flow and VFD oil-bubble flow, respectively. So, for the collected images series under certain flow condition, few misrecognition images will not impact the flow pattern recognition results.

V. CONCLUSIONS

Extracting effective and objective flow pattern features is a challenge problem in the fields of oil-water two-phase flow pattern identification. We in this paper employ deep learning method to extract oil-water two-phase flow image features and train the flow pattern identification networks. First we construct oil-water two-phase flow loop and employ high-speed camera to collect oil-water two-phase flow images. Three typical flow patterns which are oil-slug flow, oil-bubble flow and VFD oil-bubble flow have been detected in this experiment. In order to eliminate redundant information contained in the flow pattern images, we use Hough transform method to segment the original images to obtain boarders of test pipe. Then we propose a minimum gray-level searching method to locate the region of interest which can effectively reflect the flow pattern dynamic characters. In this study, we obtain totally 23000 image segmentations to train the flow pattern recognition networks. Three frequently used convolutional neural networks which are LeNet-5, AlexNet and VGG-16 net have been employed as the oil-water flow pattern identifiers. The results show that all the three recognition models have quite high identification accuracy for oil-slug flow. And the VGG-16 net with deep layer and small filters is more sensitive to VFD dispersed flow pattern than the other two networks. Employing more deep structure can extract precisely flow pattern features which is benefit for the oil-water two-phase flow pattern modeling and recognition. Our research not only provides a novel application of CNN in the oil-water two-phase flow pattern identification but also proves that deep learning theory could be a powerful tool for modeling two-phase flow system.

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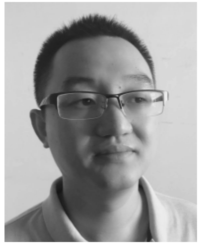

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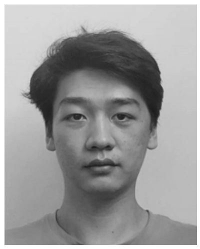

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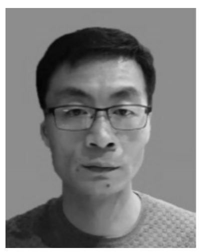

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