Water Gauge Image Augmentation based on Generative Adversarial Network

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***Abstract*—Water level monitoring based on water gauge is a very widely used way because of its cheapness and portability. However, the insufficiency and low quality of water gauge images restrict the performance of water level measuring task based on deep learning methods such as object detection and semantic segmentation. In this article, we proposed a generative adversarial network (GAN) named Contextual adjustment GAN (CA-GAN) for data augmentation of water gauge images obtained from Wuyuan, Jiangxi Province in China, i.e. CA-GAN can generate high-quality images containing various scales and types water gauge, which provide image data for application such as deep-learning based water level measuring method. First, a improved downsampling module is designed with the help of segmentation map for the semantic activation modulation. Then, the Unet++ structure with the improved downsampling module is applied in the generator. Finally, to modulate the semantic relationship, a contextual adjustment scheme is designed between adjacent layers. This article conducts detailed experiments, proving that the improved downsampling module contributes to the maintenance of semantic information of water gauge images. It is illustrated that the water gauge images generated by CA-GAN have higher quality comparing with other three GAN models. And our method is expected to promote the water level measurement and hydrological monitoring application development.**

***Index Terms*—data augmentation; hydrological monitoring; deep learning; generative adversarial network**

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I. INTRODUCTION

Hydrological monitoring refers to a complex and comprehensive system engineering that monitors, measures, analyzes, and warns of the temporal and spatial distribution and changing laws of natural water through scientific methods. For particular, it includes the process or real-time detecting and measuring the hydrological parameters at specific locations such as rivers and lakes [1] [2]. Hydrological monitoring plays an important role in the fields of soil and water conservation and water-related disaster prediction. With the development of edge intelligence [3], hydrological stations show great potential for developing smart and IoT systems [4]. One important subtask of hydrological monitoring is river water level measurement.

As a common measurement tool, water gauge is widely used in hydrological monitoring. The water gauge is usually erected by the river or water-related places, and water level monitoring exploits water gauge images taken by a camera. The water gauge is composed of numbers and characters E in a regular arrangement. The current water level value needs to be obtained from the number and character information above the water surface. The digital markers determine the rough water level value information. Since there are still some distances between each digital marker, the precise segmentation of the water level line is the key to improve the accuracy of the water level value. In general, we need to find out the area of the water ruler and the area of the number marker from the water ruler picture, and then determine which number marker is respectively. The hydrological data such as water level values are often stored and analyzed in IoT system, and is expected to be gathered with vehicle mounted units [5]. In order to solve the problem of water level value recognition, some computer

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vision and image processing algorithms are applied in this application. Comparing with the traditional image processing methods, the applicable scenarios of deep learning method are various, as the artificially designed feature extractor does not perform well on water gauge detection in real complex scenes. While deep learning algorithms have a dominant advantage in computer vision tasks, it requires large amounts of data to train the models. In the field of water level measurement, it is difficult to obtain samples. Therefore, data augmentation applied to the water gauge image domain is necessary.

Aiming at the problem of lacking samples in the image processing tasks, many data augmentation methods in computer vision techniques have been proposed. However, many existing data augmentation methods only apply affine transformation such as zooming, cropping, flipping, rotating [6], ignoring semantic information of water gauge images. The essence of these methods is just some geometric transformation or simple reorganization of the pixel values for each image channel, which can no longer fulfill the increasingly requirements in the task of object detection, segmentation and water level measurement of water gauge images.

In recent years, a number of artificial intelligence or deep learning based data augmentation methods have been proposed to improve the data augmentation performance. The autoencoder(AE) is a typical feature learning method. Lv et al. [7] introduced stacked contractive autoencoder(sCAE) to extract the temporal varing feature from superpixel. The variational autoencoder (VAE) [8] realize the mapping from a vector to real data in a high-dimensional space. However, VAE optimizes variational lower bound of possibilities, which lead to blurrier and lower quality samples.

NASIRI S et al. [9] introduce noise into images to change the high-frequency feature of original images. The deep learning based augmentation strategy achieves higher quality than traditional methods, and represents great potential in image detection and segmentation tasks. But many deep learning methods are supervised of large datasets, water level measurement also relys on image dataset for model training, leading to the limitation on the application of these methods. In addition, manual labeling will unavoidably introduce noisy annotations, which will affect the training of the model and the accuracy of the water level value measurement.

To address these limitations, generative adversarial networks (GAN) [10] is proposed to generate realistic samples on image datasets. GAN takes randomly distributed noise as input, and the generator and discriminator are trained at the same time.in a minimax algorithm. Due to the remarkable image generation results of GANs, it has gradually become a propular issue in the field of data generation, and many improvement methods have been proposed later. Conditional GAN (cGAN) is proposed to actively decide certain properties of generated images. Mirza [11] proposed cGAN that exploit conditional information as constraint and label images automatically. But the lack of semantic information remained a problem in application on GANs.

Therefore, this article focuses on data augmentation method of water gauge images with GAN model based on the water gauge images of Wuyuan, Jiangxi Province in China. We proposed a new water gauge images generation model, named Contextual adjustment GAN(CA-GAN), which can provide data support for the application on water level measurement. The main contributions of our research are as follows:

(1) To label the water gauge images automatically, this article combined image segmentation map and random noise as the network input.
(2) To improve the quality of generated water gauge images, this article introduced the semantic segmentation map to generate attentive layer activations.
(3) To revise the semantic relationship of adjacent feature layers during image generation, this article proposed a contextual adjustment module, which capture the high semantic from the high-level feature map and conduct contextual semantic adjustment on the lower feature map.

To validate the effectiveness of CA-GAN, the water gauge images of Jiangxi Province was chosen as experimental data in this article. Results show that CA-GAN is able to generate water gauge images with higher quality and then contribute to deep-learning based water level measurement method development.

II. RELATED THEORY

Many data augmentation methods based on deep learning have been proposed to solve the problem of lacking samples in the image processing tasks.

A. Generative adversial networks

Data generation based on deep learning is an essential task that promises to promote the development of unsupervised learning field. Generating adversarial networks is a typical example of unsupervised learning. Goodfellow et al. proposed GAN and opened up a new paradigm for data augmentation and generative model. Radford proposed DCGAN [12], which is the improved variant of GAN. The generator and discriminator learn to represent the input image hierarchically, respectively. WGAN [13] uses Earth-Mover instead of Jensen-Shannon scatter to measure the distance between the real and generated sample distributions. GAN suffers from the gradient vanishing problem when training based on gradient descent, resulting in a discontinuous optimization objective. To solve the problem of vanishing training gradients, Arjovsky et al. proposed the Wasserstein GAN [13]. In order to solve the two shortcomings of poor quality of images generated by standard GANs and the instability of the training process, LsGANs [14] performs well by replacing the cross-entropy loss with the least-squares loss. But these methods have less contribution on the semantic information supplement.

B. Structed semantic information loss

Image-to-image translation tasks based on cGAN are often composed of deep convolutional networks(DCN). DCN has powerful capabilities in image feature processing, but it often leads to semantic information loss. Further, each output pixel in cGAN is not considered independent from all others given the input image, resulting in structured semantic information loss. Unet [15] applies long skip connection to reduce information loss caused by downsampling. To solve the problem, Spatially-Adaptive normalization (SPADE) [16] was proposed with BatchNormalization [17]. Inspired by the idea of the SPADE module, improving the downsampling module in the Unet structure is a possible solution. In addition, the idea of cross-layer attention transfer from [18] is also valid.

III. METHOD

The method proposed is dependent on actual water gauge images generation requirements. As of now, the majority of the exploration on image generation centers around the regular nature image, while no research on water gauge image generation. Subsequently, the current research results can not be straightforwardly utilized in this article, and the generation model should be determined bit by bit. Automatically generated label and quality of the generated water gauge image are important for water gauge image generation task, so the method CA-GAN is proposed according to the application requirements.

A. Labels of Generated Water Gauge Images

As the insufficiency of corresponding labels of generated data, ISOLA P [19] proposed the idea that input image segmentation maps to the generator. But the prerequisite is that the segmentation map outline need to be fine enough. To solve the problem, the CA-GAN selected image segmentation map, which is set as label, combined with noise as input to the generator. Figure 1 shows the input of the proposed model CA-GAN in this article.

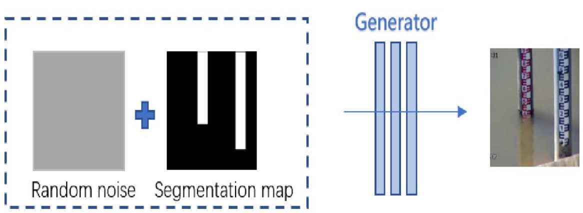

Fig. 1. Input of CA-GAN's generator.

B. Improve the Downsampling Module of the Network

The generated water gauge images with traditional method is of low quality, so fully utilizing the information and reducing semantic loss are necessary in water gauge image generation task. CA-GAN is based on Unet++ network [20] for its effective exploitation of image information.

But Unet++ also has limitation, the four downsampling modules of the network during the encoding procedure bring about the great loss of semantic information. Research has indicated that using batch normalization and instance normalization layers will cause deficiency of semantic information.

To reduce above information loss from standardization layer in the downsampling modules, segmentation map is applied to improve the semantic information during the encoding network. And the proposed downsampling module is shown in Figure 2.

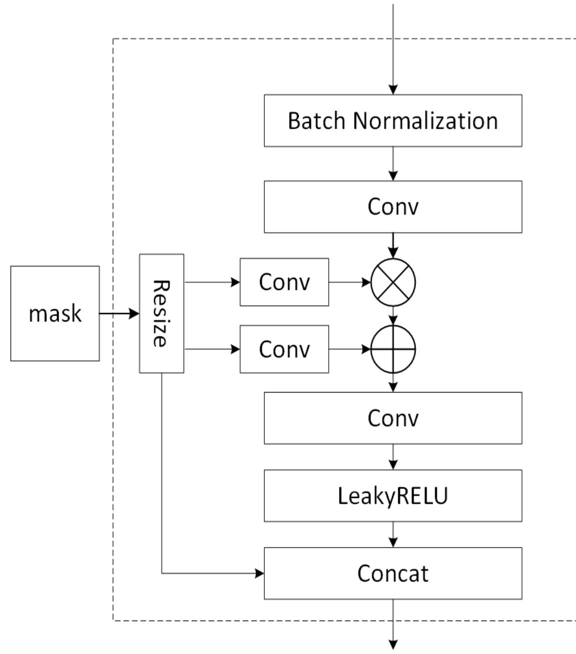

Fig. 2. The proposed downsampling module.

C. Reduce the Semantic Information Loss

The encoder of the CA-GAN model fully extracts the semantic features of the original data and the decoder uses these features for the reconstruction of the image to generate a new water scale image. In order to extract better features, deep convolutional neural network is used as the decoder. How to efficiently use the feature maps generated by the encoder is also the main issue of our research. Feature layers of different heights contain different levels of semantic information, with features at lower levels containing rich image details and features at higher levels containing global semantic structure information. Therefore, we fuse the feature maps between adjacent layers to fully preserve the semantic information in the source images. Based on this idea, we propose the contextual adjustment module. CA produces dense pixel-level contextual information while improving the efficiency of feature encoding in long connected paths. The contextual adjustment module is shown in Figure 3.

To improve the generator network, CA-GAN modified the input of network and introduced the contextual adjustment module in the model. The generator structure of CA-GAN model is illustrated as Figure 4. In Figure 4, cyan squares is the proposed downsampling module, and yellow squares represent the contextual adjustment module. The black dotted lines represent the skip connection in Unet++ network.

The discriminator of CA-GAN is shown in Figure 5, based on the convolution neural network(CNN). In Figure 5, the

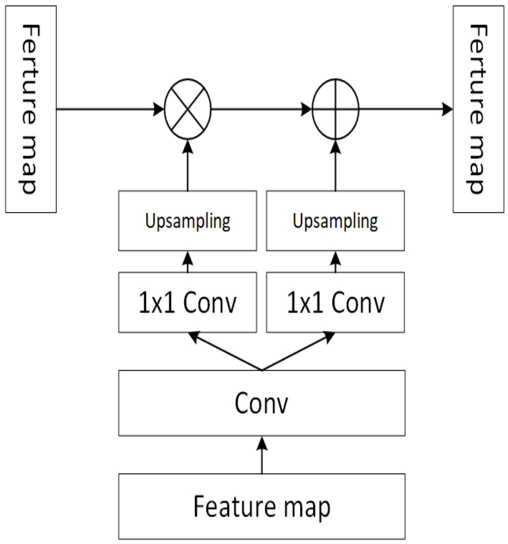

Fig. 3. Contextual adjustment module.

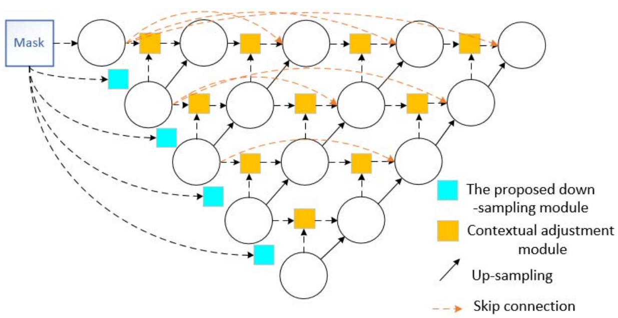

Fig. 4. Generator network structure of CA-GAN.

inputs of the discriminator are the water gauge image and its corresponding segmentation map, and output is final determination result. The size of water gauge images and segmentation map in this article are both 256×256.

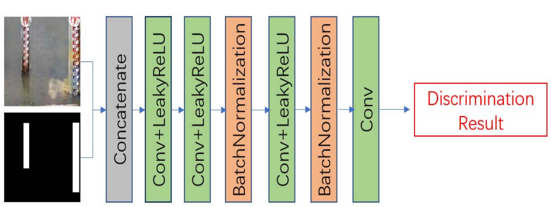

Fig. 5. Discriminator network structure of CA-GAN.

D. The Structure of CA-GAN

According to the actual demand of water gauge image generation, CA-GAN is constructed step by step. The full structure of CA-GAN is shown in Figure 6.

In Figure 6, the dotted box denotes the generator structure of CA-GAN. Cyan square denotes the downsampling module and yellow square denotes the contextual adjustment module. The mask square represents the segmentation map, making up the input of the generator with noise. The orange squares represents the discriminators. The black dotted lines represent the skip connection in Unet++ network. Between the encoder and decoder in the generator, there are many layers designed for the "dense connection". The contextual adjustment plays a role of semantic connector. These modules capture the semantic information from the high-level feature map and conduct contextual semantic adjustment on the lower feature map. The process could help the feature fuse efficiently and reduce the semantic information loss.

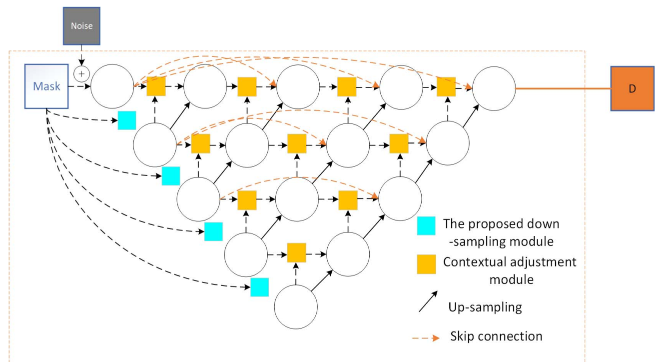

Fig. 6. Discriminator network structure of CA-GAN.

E. Loss function of CA-GAN

Suppose that G denote the generator, x denote the segmentation map, z denote the noise, then $G(x, z)$ denote the output of generator. Let D denote the discriminator, y denote the original water gauge image.

Generally, CA-GAN belongs to the condition GAN. The loss function of CA-GAN can be defined as (1):

$$\begin{aligned}\mathcal{L}_{CA-GAN}(G, D) = \mathbb{E}_{xy}[logD(x, y)]+ \\ \mathbb{E}_{x,z}[log(1 - D(x, G(x, z)))]\end{aligned} \tag{1}$$

Where aim of G is to minimize this loss, which of D is to maximize it, that is (2):

$$G^* = arg\, min_G\ max_D\ \mathcal{L}_{CA-GAN}(G, D) \tag{2}$$

Where min_G refers to minimum the loss of generator, and max_D refers to maximize the loss of discriminator.

Most researches have found that mixing the GAN loss function with Euclidean distance is useful, such as L1 distance and L2 distance. For the purpose of less blurring, we also apply the L1 distance for the function (3):

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{xyz}[\|y - G(x, z)\|_1] \tag{3}$$

Then our final loss function can be expressed as (4):

$$G^* = arg\, min_G\ max_D\ \mathcal{L}_{cGAN}(G, D) + \lambda\mathcal{L}_{L1}(G) \tag{4}$$

Where λ represents the weight of two terms. It is a super parameter, which can be adjusted according to the situation.

IV. EXPERIMENTS AND RESULTS

A. Dataset

Since there is no public dataset for the water gauge image, we only train and evaluation it on our water gauge dataset. Most of the actual water gauge data come from the hydrological station's system in Wuyuan, Jiangxi Province. Images are cropped into a water gauge dataset with the resolution of each image of $N \times N$, where N is selected as 256 in the experiment. We collected 560 water gauge images from monitoring sites in this system. Besides, we also download gauge images from the internet and also get 200 water gauge images. We also perform geometric transformation on the image to expand the dataset, including flipping, rotating, cropping, deforming, zooming, etc. Then we annotate gauge and printed numbers with 12 classes and crop the raw image to a small size. As a result, we create the training and test split, with 5.6k and 0.6k images respectively. The samples of dataset are shown in Figure 7.

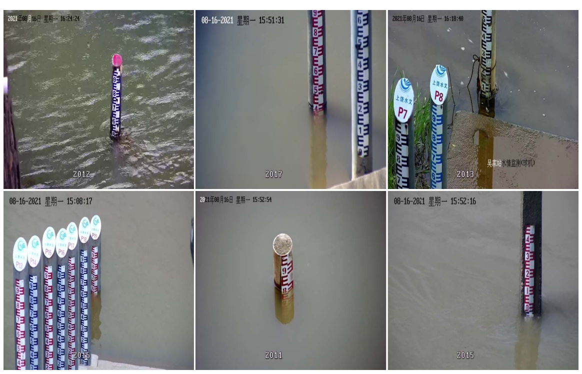

Fig. 7. Samples of the water gauge dataset

B. Evaluation

In recent research, the evaluation criterion for image generation is still controversial. A traditional method is judging image generated subjectively, but is less rigorous in science. An effective method is using image segmentation methdos to evaluate the generation quality [21] [22]. The FCN-8s [23] is chosen in this article to complete segmentation task based on the generated images. Theoretically, the higher the generation quality is, the better segmentation effect becomes. In other words, the higher segmentation score represents, the better the quality of the generated image. Therefore, segmentation scores are chosen as evaluation criteria in this article, including pixel accuracy, class accuracy and IoU.

Suppose that the account of sample classes is n, P_{ii} denotes the account of class pixels correctly predicted, P_{ij} denotes the pixel account of class i_{th} wrongly predicted as class j_{th}, P_{ji} denotes the pixel account of class j_{th} wrongly predicted as class i_{th}.

(1) Pixel Accuracy is the total account of correctly segmented pixels divided by the total account of pixels, that is, the percentage of correctly segmented pixels in the image. The pixel accuracy is defined as (5):

$$PixelAccuracy = \frac{\sum_{i=1}^{n} P_{ii}}{\sum_{i=1}^{n}\sum_{j=1}^{n}(P_{ij} + P_{ij})} \tag{5}$$

(2) Class Accuracy is the ratio of correctly predicted pixels account to total predicted pixels account in this class. The class accuracy of the i_{th} class is defined as (6):

$$ClassAccuracy = \frac{\sum_{i=1}^{n} P_{ii}}{\sum_{i=1}^{n}\sum_{j=1}^{n}(P_{ii} + P_{ij})} \tag{6}$$

(3) IoU is the intersection of the correctly predicted pixels and the predicted pixels divided by the union of them. The IoU of class i_{th} pixels is defined as (7):

$$IoU = \frac{P_{ij}}{\sum_{j=1}^{n} P_{ij} + \sum_{j=1, j\neq i}^{n} P_{ji}} \tag{7}$$

C. Experiment and Analysis

The experiment are divided into three sub-experiments. The first two experiments are designed to test the validity of proposed downsampling module and contextual adjustment module respectively. The third experiment compares the segmentation performance on images generated by CA-GAN model and three widely used GAN models.

1) Downsampling module experiment: To validate the effectiveness of proposed downsampling module, the original structure and improved structure are used to generate water gauge images respectively. The difference of network structure of the two CA-GAN models is existence of downsampling module. The CA-GAN without any proposed modules is used as the base network. The two tested networks are CA-GAN/wo DS and CA-GAN/w DS. The discriminator structure of both is the same. The CA-GAN/w network is equipped with the improved downsampling module in the generator, while the CA-GAN/wo network is not. The two networks are trained on the above datasets. The training parameters of the two models keep the same value, as listed in Table I.

TABLE I
CA-GAN'S PARAMETERS SETTING IN TRAINING

Parameters	Value
image size	256 × 256
iterations	5000
batch size	5
epochs	70
learning rate	0.0002
optimizer	Adam
activation	Leaky RELU

The model FCN-8s is trained on our water gauge image dataset to segment the generated water gauge images. And pixel accuracy, class accuracy, IoU are calculated as the evaluating criterion, listed in Table II. Two different models are showed with and without the improved downsampling module. DS represent the improved downsampling module.

TABLE II
FCN-SCORES FOR DOWM-SAMPLING MODULE

Model	Pixel Accuracy	Class Accuracy	IoU
CA-GAN/wo DS	0.41	0.13	0.11
CA-GAN/w DS	0.50	0.20	0.14

2) Contextual adjustment module experiment: Secondly, we conduct the experiment to test the effectiveness of the contextual adjustment module. We use CA-GAN without any proposed modules as the base network. The two tested networks are CA-GAN/wo CA and CA-GAN/w CA. The discriminator structure of both is the same. The CA-GAN/w network is equipped with the contextual adjustment module in the generator. The CA-GAN/wo network is not equipped with the contextual adjustment module in the generator. The two networks are trained on the above datasets. Then the samples generated by the two networks were used as the training set respectively. And the segmentation result of FCN-8s is shown in Table III.

TABLE III
FCN SCORES FOR CONTEXTUAL ADJUSTMENT MODULE

Model	Pixel Accuracy	Class Accuracy	IOU
CA-GAN/wo CA	0.41	0.13	0.11
CA-GAN/w CA	0.53	0.22	0.15

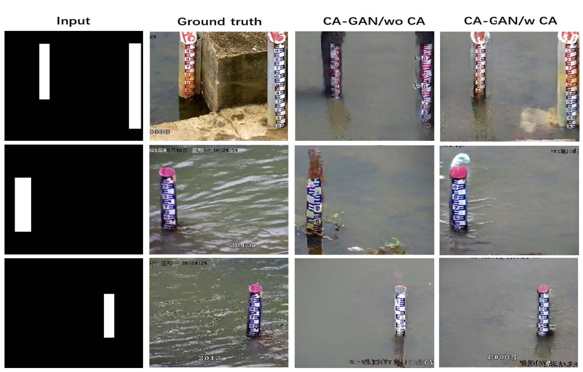

Fig. 8. Qualitative result of different architecture with CA module

For the qualitative result of contextual adjustment module, this article use the two models to generate real water gauge images. Figure shows the different performance of the two model with and without CA module.

Table III shows that CA-GAN/w CA achieves higher scores than CA-GAN/wo CA. Figure 8 shows the qualitative result of different CA-GAN architecture. CA-GAN/wo CA leads to less semantic reconstruction ability. CA-GAN/w leads to more semantic reconstruction ability and clearer images. The two results demonstrate the effectiveness of the contextual adjustment module.

3) CA-GAN VS other GAN experiment: After the two experiments about downsampling and contextual adjustment module demonstrate their effectiveness, the final full CA-GAN is prepared as whole model. Then, this article also compare CA-GAN with other different methods, including CoGAN [24], SimGAN [25], and CycleGAN [26] on data scraped from our Datasets.

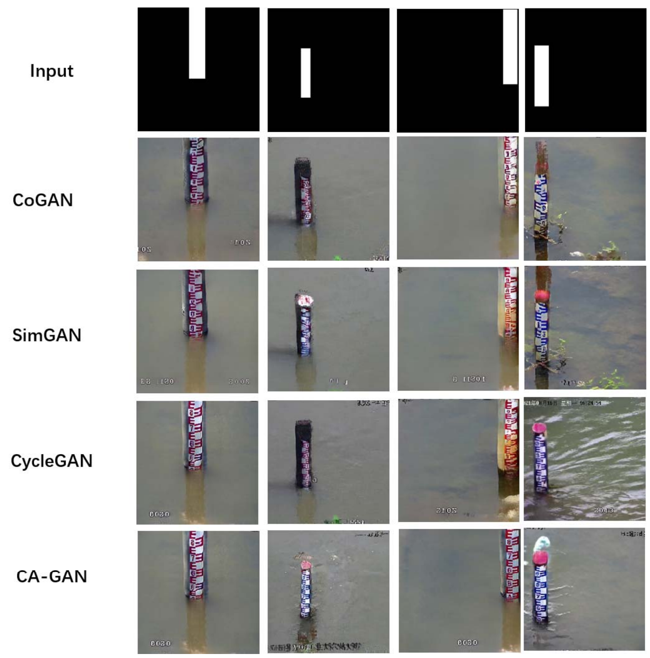

Fig. 9. Qualitative result of different models

TABLE IV
FCN-SCORES FOR DIFFERENT METHODS

Model	Pixel Accuracy	Class Accuracy	IoU
CoGAN	0.24	0.08	0.04
SimGAN	0.26	0.10	0.05
CycleGAN	0.46	0.13	0.11
CA-GAN	0.55	0.19	0.14

Table IV and Figure 9 show the performance of our method comparing with other methods. The generator of CA-GAN is based on Unet++ and adopted with the improved downsampling module and contextual adjustment module. The proposed downsampling module helps to reduce the semantic information loss and efficiently encode the conditional semantic segmentation map feature into the GAN encoder. The dense connection structure of Unet++ helps combine deep and shallow feature. The contextual adjustment module uses high-level semantic features to advise the low-level feature and learn how to borrow or copy semantic information from an adjacent feature map. The adjustment of semantic information can be transmitted to the end of the generator through the network feature stream.

V. CONCLUSION

To solve problems caused by low quality in the task of water gauge image generation, we propose a deep adversarial network-based water gauge image generation model called CA-GAN. The "dense connection" structure of Unet++ is chosen in this article to extract deep and shallow features, and the improved downsampling module and contextual adjustment module are introduced to improve the quality of generated water gauge images. The generated label can be obtained at the same time of generating the image. The downsampling module introduces the segmentation image as a conditional label, while alleviating the semantic loss caused by the downsampling process. The context adjustment module acts as a feature fusion model to fuse the semantic features at the lower level with the semantic features at the higher level. This module generates dense contextual feature information to meet the semantic requirements in the image reconstruction process. The experimental results on the actual data set of water gauges from hydrological station's system show that the proposed CA-GAN outperforms other generation models in image quality. Therefore, our method is expected to improve the performance of deep-learning methods applying to water level measurement tasks, which contributes a lot to hydrological monitoring and the smart city construction [27].

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