A novel method of automatic reading for rotor water meter based on image processing

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Abstract: This paper investigates the issue of the reading of rotor water meters and presents a novel method of automatic reading based on image processing. In order to handle the impact of complex environment, we use object detection neural network to detect the bounding boxes of sub-dials on the water meter. Based on the standard spatial layout of sub-dials, the pose of water meter is corrected by perspective transformation. The regions of pointers are segmented from sub-dials by semantic segmentation. According to the segmented region, a multi-centroids method is proposed, through which the angle of the pointer area can be accurately obtained. The proposed method of automatic reading has better robustness and the obtained readings are more accurate. Simulation study is conducted to verify the effectiveness of the proposed method.

Keywords: rotor water meter; automatic reading; deep learning; image processing; multi-centroids method.

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1 Introduction

With the smart city initiatives, artificial intelligence, big data and cloud computing technologies (Chen and Gennaro, 2018) have developed rapidly in this area. The smart applications include water supply, transportation and other public utilities. Currectly, the water utility company reads and maintains meters regularly, which may lead to waste of resource management and brings inconvenience to users. In order to obtain reading of water meter, engineers have proposed some methods, which are divided into two categories:

1 installing new remote water meter with embedded device (Li and Chong, 2019; Li et al., 2019; Suresh et al., 2017)

2 processing the uploaded image by automatic reading algorithm (Li and Sun, 2013; Meng and Cheng, 2021; Zuo et al., 2021) in the server.

Installing new water meters can achieve real-time monitoring while the cost becomes higher. By contrast, it is more convenient that users upload the images of water meters on the server with a mobile phone. Thus, it is necessary that automatic reading algorithm possesses accurate reading.

Usually, there are two kinds of water meters: rotor water meter and digital water meter. According to the water company's statistical data, rotor water meters account for half of the total number. Especially, in old districts, the proportion of rotor water meters is as high as 80%. For digital water meters, some automatic reading algorithms have been investigated (Liu et al., 2020; Yang et al., 2019; Hong et al., 2021). However, for rotor water meters, the results of the algorithms applying to complex environments are few. The complex environment includes:

1 The different installation position of water meter results in different shooting angles.

2 Due to the installation position, the working environment is usually dark. We can use the camera flash in low light, which is also easy to cause overexposure.

3 The environment is usually damp and it causes rust stains. It is difficult to clean.

The above questions are common in images. Based on the above observation, this paper studies the automatic reading issue of rotor water meter in complex environments.

The image processing technology mainly includes traditional algorithms (Baxes, 1994) and deep learning (Dhillon and Verma, 2019). For reading algorithms of the rotor water meter, the existing results (Zhang and Li, 2009; Gang and Yan, 2013; Gao et al., 2018; Di et al., 2013) are based on the traditional algorithms, and used in experimental environment. The procedure of traditional reading algorithms described as follows: First, preprocess the image of water meter; next, locate the sub-dials; then, measure the angle; finally, get the reading. However, by these traditional algorithms, the noise including rust stains and overexposure, makes the segmentation of the pointer region incomplete. The centre of sub-dial is also inaccurate, which causes the error to be bigger in complex environments, such as threshold segmentation and hough transform method. Aiming at the above problem, this paper adopts multi-centroids method and fits centroids of different pointer regions, which reduces the risk of using inaccurate centre. In the last decade, deep learning techonlogy has shown many advantages and has developed rapidly in the field of image processing, but its flexibility is poor. We firstly train the network that classifies the red and black sub-dials into 20 classes based on their readings. It is found that network is difficult to judge the reading when the pointer is on the scale. Even though a modified YOLOv3-Tiny network (Zhang et al., 2021) can been used to detect the key points on the sub-dials, the distortion of image during the shooting still can not be corrected and the risk of detected key points is high, which leads to the deformation of pointer and the inaccurate reading.

Inspired by the above discussion, this paper investigates automatic reading problem for rotor water meter based on deep learning. First, under the complex environment, we adopt deep learning to locate the sub-dials and segment the pointer regions. Second, based on the detected bounding boxes, the image of water meter is corrected. Next, for the incomplete pointer region, measuring algorithm based on the multi-centroids is presented. The algorithm can extract the main direction of pointer region accurately. Lastly, reading rule of water meter is established in terms of the people's reading method.

Comparing with the existing results (Li et al., 2021), this paper attempts to makes the following improvements: first, this paper employs new object detect network for the sub-dials detection, which quickens the velocity of algorithm and improves the location accuracy. Second, the semantic segmentation neural network is replaced from UNet to UNet++, which increases the accuracy of the segmentation. Finally, for the measuring algorithm, this paper employs multi-centroids method instead of double centroids. The multi-centroids method can extract the main direction of the incomplete pointer region more accurately and further prevent noise interference. The contrastive experiment also shows the robustness of the algorithm. The experiment result has a significant improvement.

This note is organised as follows: in Section 2, we introduce why the YOLOv4 is chosen and how water meter readings are corrected. Section 3 explains how the UNet++ works in the segmentation of pointer and presents the multi-centroids method. Section 4 describe how the dataset of water meter construct. We make simulation experiments in Section 5 and give some concluding remarks in Section 6.

2 Correcting based on YOLOv4

In order to deal with environmental change, we adopt YOLOv4 to detect the bounding boxes of the sub-dials.

According to the contrast of the bounding boxes and existing standard poses of sub-dials, we can use perspective transformation to correct the water meter.

2.1 Detecting sub-dial

In the rotor water meter, there are eight sub-dials. Before reading, we need to locate the positions of sub-dials. In the past, engineers used to adopt connected component analysis, sift match (Guo et al., 2017) or template match (Zhang et al., 2017; Hung and Hsieh, 2015). In practical applications, since the water meter works in complex environment, such as lighting and installation position, the parameters in the algorithm will vary significantly with environment. One approach to solve this problem involves the use of neural network algorithms to detect the bounding boxes of all sub-dials.

Figure 1 Detecting sub-dial (see online version for colours)

In the fields of object detection, SSD (Liu et al., 2016) and YOLO (Redmon et al., 2016) have been widely used. On the accuracy, both SSD and YOLO have good performance in the test, but the speed of YOLO is faster than that of SSD. Therefore, we adopt the YOLO. In the result of Li et al. (2021), because the priority of recall rate is higher than speed, the literature adopted YOLOv3 rather than YOLOv3-tiny, which also causes the algorithm to run more slowly, until the YOLOv4 (Bochkovskiy et al., 2020) is presented, which is the fourth generation of the YOLO series. YOLOv4 has been improved in the following three aspects:

1. YOLOv4 adopts the CSPDarknet53 as backbone to improve the efficiency of feature extration.
2. To adapt all input image sizes, YOLOv4 employs the spatial pyramid pooling (SPP) and path augmentation net (PANet) to form a feature fusion layer.
3. Activation function Mish replaces leaky-relu in YOLOv4, which has better nonlinearity.

Therefore, YOLOv4 reaches higher accuracy and faster speed than YOLOv3. In this paper, we adopt YOLOv4 to locate the the bounding box of the sub-dials.

In Figure 1, although the shooting angle is tilted, the bounding boxes of the sub-dials are still accurately detected.

2.2 Perspective transformation of water meter

When the sub-dials are detected, it is still difficult to read from inaccurate shooting angle. There are three main causes that result:

1. the water meter is not in the middle of the image
2. the water meter is not positive
3. shooting angle is not vertical.

For the first and second, the water meter can be translated and rotated to positive pose before reading. Besides the positive pose, the shooting angle should be as vertical as possible to the meter. When it is not vertical, there is a visual error (Xing et al., 2017) in the image of water meter. It is easy to cause the image of pointer to deform, which leads to obtain the wrong readings.

Perspective transformation can change the perspective of image or video to better understand information. Since the image is the projection of a three-dimensional object on a two-dimensional plane, there must be a corresponding relationship between different perspectives of the same object. Therefore, in theory, as long as we seek the corresponding and confirm the projection direction, the current perspective can be converted to the corresponding perspective.

Similarly, the shooting angle of the water meter can be corrected by perspective transformation. We choose a standard water meter as the target of the perspective transform and determine the sub-dial correspondence between the standard water meter and detected water meter. The standard counterclockwise sequences and order of the sub-dials are red, red, red, red, black, black, black, black. We also sort the detected sub-dials counterclockwise. Until the sequences and order of detected water meter become standard, the first sub-dial in the sequences is continuously placed at the end. The flow chart is shown as Figure 2. After getting correspondence, we choose four non-adjacent sub-dials from eight sub-dials of water meter and the perspective transformation matrix will be solved and the perspective transformation is performed in the water meter.

The general equation for perspective transformation (He, 2005) is as follows:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = M \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \tag{1}$$

$$x' = \frac{x}{z} = \frac{m_{11}u + m_{12}v + m_{13}}{m_{31}u + m_{32}v + m_{33}} \tag{2}$$

$$y' = \frac{y}{z} = \frac{m_{21}u + m_{22}v + m_{23}}{m_{31}u + m_{32}v + m_{33}} \tag{3}$$

where x, y and z are the coordinates in which the image coordinates are mapped to the three dimensions, matrix M

is perspective transformation matrix, u and v are initial image coordinates, x' and y' are new image coordinates.

Finally, we obtain the corrected water meter, which is shown as in Figure 3.

Figure 2 Flow chart of seeking corresponding relationship (see online version for colours)

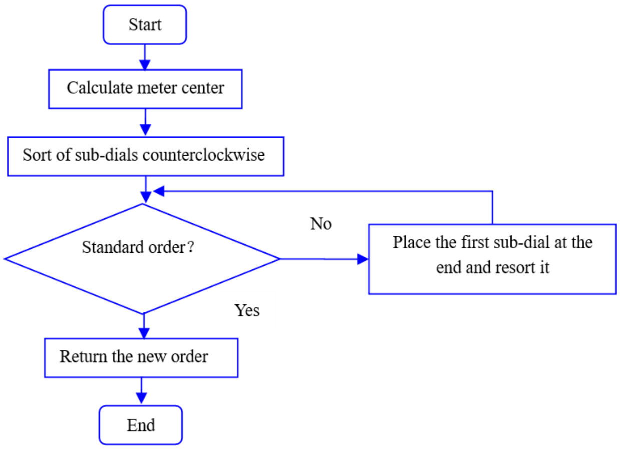
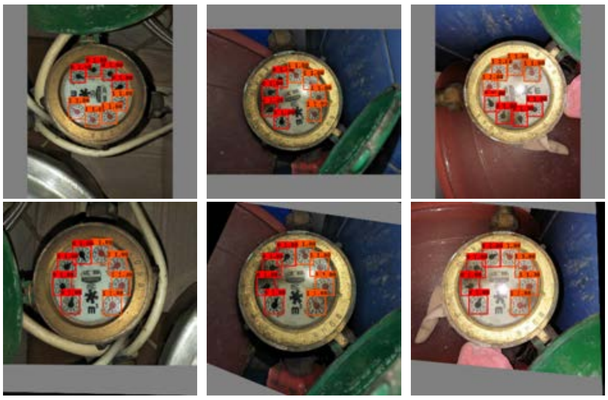


Figure 3 Water meter by perspective transformation (see online version for colours)



3 Measuring algorithm based on UNet++ and multi-centroids method

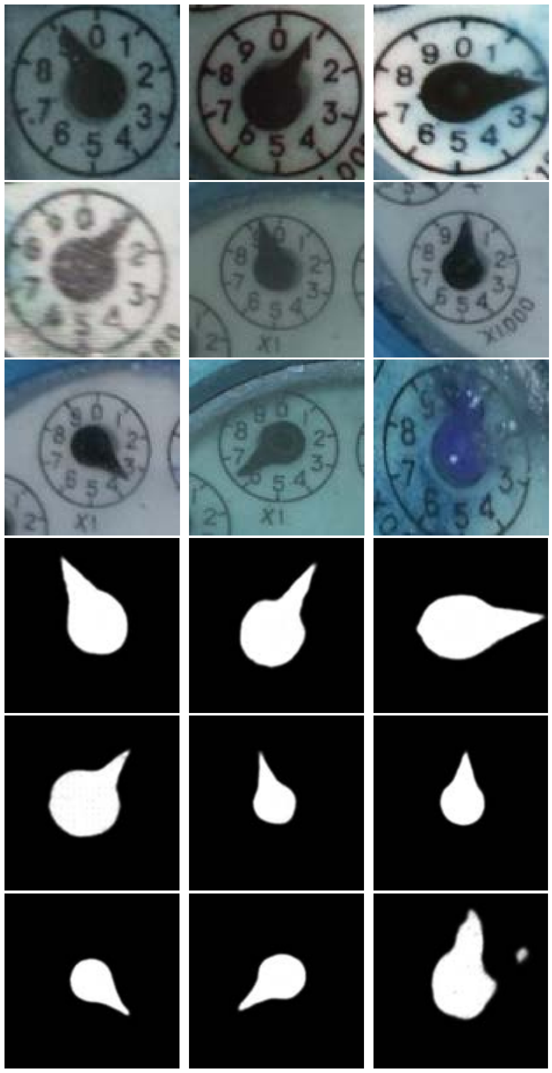
The UNet++ network has better feature reduction, which contributes to segment the regions of pointers. To accurately obtain the angles of the pointers, we propose a multi-centroids method.

3.1 Semantic segmentation of pointer

After the water meter is corrected, the angle of pointer can be used for reading. We need to know where the region of pointer is and segment it. In the field of semantic segmentation, the robustness of the traditional algorithms, such as threshold segmentation, edge detection and SVM (Zhang et al., 2017; Liu, 2015), is not strong. Once the environment changes, the algorithm effect also become worse. We also test some neural network algorithms. The representative semantic segmentation algorithms include Deeplab (Chen et al., 2018), UNet (Ronneberger et al., 2015). The Deeplab series perform better in the global feature extraction. The UNet series are suitable to extract the local features. Since the feature of pointer regions is relatively simple, the UNet series are more suitable.

The UNet++ (Zhou et al., 2020) is a neural network updated from U-Net for semantic segmentation. The UNet++ improves segmentation architecture based on nested and dense skip connections, which makes the local feature of image to be segmented better than U-Net. On the other hand, the improvement of architecture adds many parameters. Too many parameters of UNet++ make back propagation difficult and make the speed of forward propagation more slow. To reduce the number of parameters, we prune some channels, which increases dramatically the speed of forward propagation and back propagation.

Figure 4 Pointer segmentation (see online version for colours)

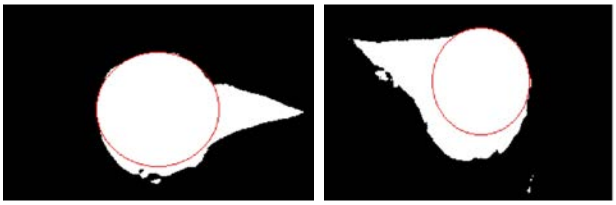


The trained UNet++ can segment more accurately the regions of the pointers. The result of semantic segmentation is shown in Figure 4. It is observed that the edge of the pointer region is more smooth than in Li et al. (2021).

3.2 Measuring pointer angle by multi-centroids method

In fact, in order to measure pointer angle, we have attempted to use some methods such as convex hull (Yan et al., 2018), template matching (Zhang et al., 2017; Hung and Hsieh, 2015) and Hough circle (Chang et al., 2018). Their effect is still unsatisfying and these algorithms depend on the geometric features of pointer region. Even though the pointers have been segmented by UNet++, the regions may still be incomplete and distortion, due to rust stains, overexposure and shoot angle. As shown in Figure 5, taking the Hough circle algorithm as an example, when the base of the pointer is incomplete and distorted, it is difficult to locate the centre. The double centroids method (Li et al., 2021) uses the centroid to avoid the defect of geometric features, but it still has some errors when pointer region is imcomplete. Therefore, in order to measure the angle, we present a new multi-centroids method improved from the double centroids method. The double centroids method is a special case of multi-centroids method. This method is able to adjust the errors.

Figure 5 Results in Hough circle algorithm (see online version for colours)



The steps of multi-centroids method are as follows: First, the largest region would be retained in the segment regions, which is the pointer region. The centroid of the region can be obtained by equation (4). Second, we draw some solid circles centred on this centroid with different radii to cover the region of pointer. Third, by the equation (4), we calculate the centroids of the rest region in turn. Finally, the main direction of the pointer can be linearly fitted by these centroids.

$$x_c = \frac{\sum_{i=1}^{n} p_i x_i}{\sum_{i=1}^{n} p_i} \quad y_c = \frac{\sum_{i=1}^{n} p_i y_i}{\sum_{i=1}^{n} p_i} \tag{4}$$

The minimum radius is greater than the minimum distance from the centroid to the pointer boundary and less than the maximum distance from the centroid to the pointer boundary. Figure 6 shows once the centroid deviates from the main direction, it causes solid circles to cover more and more areas on the other side of the main direction, which makes the centroids of the rest region converge along the main direction.

Obviously, from Figure 7, we can obtain the more accurate main direction by multi-centroids method.

3.3 Pointer reading recognition

The sub-dial is masked with 0–9 according to the angles. Hence, the readings are divided into ten classes. The relationship between angles and readings is given, as shown in Table 1.

Figure 6 Multi-centroids method

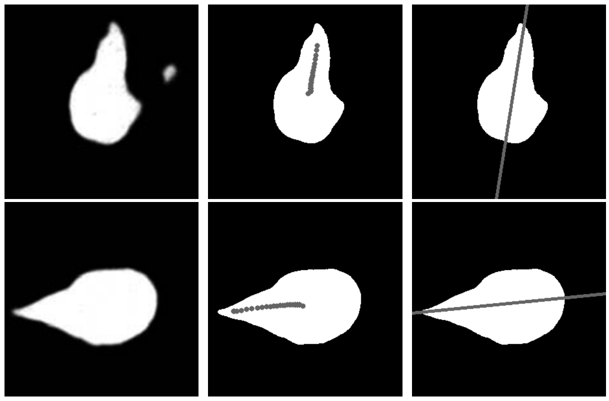


Figure 7 Results in multi-centroids method

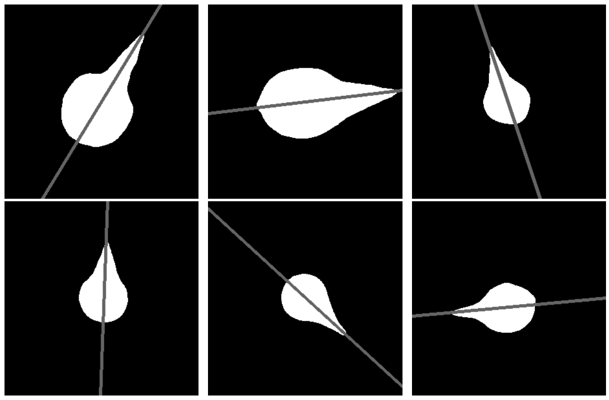
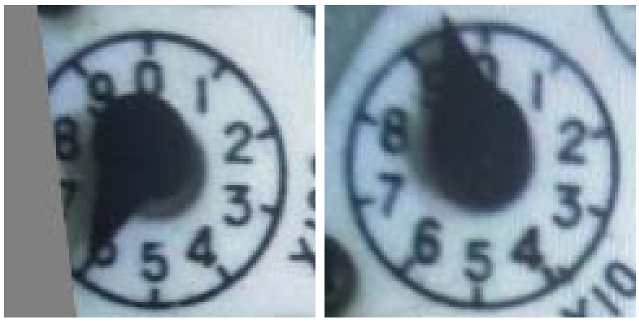


Figure 8 Reading of sub-dial (see online version for colours)



However, when the angle is near the critical value, it is difficult to judge the reading. According to reading method, we can judge the angle by observing previous dial. When the difference between the current pointer angle and the previous scale is less than 5, if the previous reading is less than zero, the reading will be abdicated, else the reading will keep the current state. When the difference between the current pointer angle and the previous scale is more than 31, if its previous reading is more than zero, the reading can keep the current state, else will be carried. A rule table is shown in Table 2.

For example, in Figure 8, the left image is the sub-dial to be read, the right image is the previous sub-dial. Firstly, the angle in the left image is 217.5. According to Table 1, we know that the initial reading is 6, but the angle is near the critical value of 216. According to Table 2, the difference between the current pointer angle and the previous scale is less than 5, which makes us have to further judge. Secondly, by observing previous dial, it means that reading should be abdicated, as the angle of previous pointer less than 0. Finally, the reading is corrected to 5.

Table 1 Reading rule table

Angle	*Reading*	*Angle*	*Reading*
[0, 36)	0	[180, 216)	5
[36, 72)	1	[216, 252)	6
[72, 108)	2	[252, 288)	7
[108, 144)	3	[252, 288)	8
[144, 180)	4	[324, 360)	9

Table 2 Carry and abdicate rule table

Current pointer angle difference	*Previous pointer angle*	
	Angle < 0	*Angle > 0*
Angle difference < 5	–1	0
Angle difference > 31	0	+1

4 Dataset and experimental configurations

In this section, we introduce the preparation of datasets, model parameters and experiment configurations. For our pipeline's robustness under different environments, some parameter adjustment and data enhancement are carried out in the training.

4.1 Dataset description and model parameters

The image datasets of the rotor water meter come from Shenyang Water Conservancy Bureau in this paper. We pick 2,000 images from them and annotate the datasets through labelimg and labelme.

For YOLOv4, we first annotate the bounding box of sub-dials at the original image of water meter with labelimg. The label of red sub-dials is 0. The label of black sub-dials is 1. Then, in train, it is found the YOLOv4 can not detect sub-dials in all directions at times. Aiming at improving the performance of the YOLOv4 and maintaining the balance of samples in all directions, we adopt three rotation data augmentations. Data augmentations are generally used in small datasets. It is mainly used to expand the datasets and reduce the proportion of unrelated features of the dataset. The common methods of data augmentations include flip, translation, rotation, scaling and cropping. The principle is to enrich the learning of related features or reduce the learning of unrelated features in the network by adjusting the proportion of dataset. The initial trained model is sensitive to position due to the unbalanced distribution feature. After rotation data augmentations, it is realised that the features are evenly distributed in all directions. Since the validation set and testing set cannot overlap with the training set, we use rotation data augmentation in training set. The 90% of the images are divided into the training set, 5% into the validation set and 5% into the testing set.

During the training of the YOLOv4, the initial learning rate is 0.0001. The optimiser is Adam. The ema decay is 0.9998. We use three different gradient descent methods to train the network for making the loss function converge to a minimum value.

For UNet++, we pick the 1,284 images of clean sub-dials corrected by YOLOv4 and annotate the pointer regions in the images of sub-dials by labelme. The red and black pointers are annotated into one class. Specially, we should note that the pointer regions of other sub-dials are also annotated. In addition, to increase the segmented performance of the network and reduce the influence of instrument dial feature on pointer segmentation, dataset adds some negative samples which are the sub-dials without pointer.. The 90% of the images are divided into the training set, 5% into the validation set and 5% into the testing set.

During the training of the UNet++, the initial learning rate is 0.0001. The optimiser is Adam. The the loss funtion is binary crossentropy. We use the gradient descent method to train the model for making the loss function converge to a minimum value.

4.2 Hardware and software configuration

The experimental hardware configuration includes Intel 10700k cpu, NVIDIA GeForce GTX1080Ti GPU, and the software system includes Windows 10 system, CUDA 10.1, cuDNN 7.6.5, TensorFlow-GPU 1.13.2 and Keras 2.2.2.

5 Simulation experiment

This section, we use evaluation metrics to evaluate the training results of neural networks. Through the simulation experiment, we demonstrate the effectiveness of method proposed in this paper.

5.1 Training results

The YOLOv4 and UNet++ network are compiled on the keras framework.

For YOLOv4, we use mean average precision (mAP) as evaluation metrics of the network.

For UNet++, we use mean pixel accuracy (mPA) as evaluation metrics of the network.

The results of the test set are shown in Table 3.

It is remarkable that the mPA in the UNet++ is still 0.899, but in the image the pointer region is more accurate than UNet. In the literature of Li et al. (2021), there is some noise in the segmentation image and the pointer boundary is not smooth.

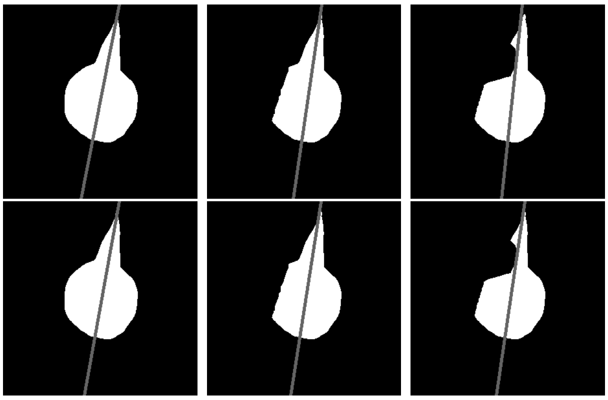
Table 3 Deep learning net models

Network model	*mPA*	*mAP*
YOLOv4		0.995
UNet++	0.899	

5.2 Contrastive results

We conduct a contrastive experiment between the double centroids method and the multi-centroids method. Firstly, some images are edited manually and deleted different positions in the image. These images are processed by two algorithms respectively. In Figure 9, the images above are processed by double centroids method and the images below are processed by multi-centroids method. Based on the 0 scale, the angles processed by double centroids method are individually 11.069, 8.329, 6.002 and in the images below are individually 10.204, 8.998, 8.398. The double centroids method is more sensitive to defects of pointer region than the multi-centroids method. Based on the analysis above, the multi-centroids method shows its robustness.

Figure 9 Double centroids method and multi-centroids method



5.3 Simulation results

Based on Zhang and Li (2009), many traditional image processing algorithms are studied to process the water meter and obtain readings. It is difficult to locate the sub-dials and segment the pointer region. The end-to-end (Chao et al., 2021) neural network model (Zuo et al., 2021; Zou et al., 2021) is also tested. When the pointer is on the scale, it is not accurate. Therefore, the algorithm is divided into object detection, semantic segmentation and pointer reading recognition.

We prepare 200 images of rotor water meter. First, these images are read by professional water meter reader. It is found there are 47 broken pointers. Then, the algorithm proposed in this paper and other algorithms are tested in the images respectively. In the result of this paper, only six readings of the sub-dials are wrong except broken pointers. The results of the algorithm are shown in Figure 2. The accuracy is 99.61%. On a computer with gpu of NVIDIA GTX2060, it takes 38 seconds. Compared with other algorithms in Table 4, the experiments show that the algorithm in this paper has faster speed and the higher accuracy.

Figure 10 Results of the algorithm (see online version for colours)

Table 4 Algorithm performance evaluation and comparison

Algorithm	*Time (s)*	*Accuracy (%)*
SVM (Zhang et al., 2017)	0.20	82.4
YOLOv3-tiny (Zhang et al., 2021)	0.15	93.7
Double centroid (Li et al., 2021)	0.25	99.3
This paper	0.19	99.6

6 Conclusions

This paper proposes a novel method of automatic reading for rotor water meter based on deep learning. First, this paper employs YOLOv4 to detect the bounding boxes of the sub-dials and it can speed up the algorithm and improve the location accuracy. Second, this paper adopts the semantic segmentation neural network UNet++, which increases the accuracy of the segmentation. Finally, this paper presents multi-centroids method for the measuring algorithm which can extract the main direction of the incomplete pointer region more accurately. The presented method achieves better performance of robustness and accuracy in our dataset. The contrastive experiment also shows the presented method is effective. In future, we will attempt to investigate a more intelligent reading method for rotor water meter.

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