An Automatic Pointer Meter Reading Method based on Deep Learning in Gas Gathering Station

Tao Zhou¹, HaiKun Wei¹ and Kanjian Zhang¹,*

¹ School of automation, Southeast University Nanjing, 210018, China

Abstract. pointer meters are widely used in gas gathering stations, and manual meter reading is time-consuming and laborious. This paper proposes an automatic reading method of pointer meters in gas gathering stations based on deep learning and image processing algorithm. Firstly, the input image is detected by YOLO neural network algorithm to quickly locate the position of the pointer meter in the image; then, the meter image is segmented from the background image, and after filtering and binarization preprocessing, the meter border is preliminarily detected by Hough transform. After further removing the background interference, the pointer area and scale value area are segmented by connected domain detection to detect. After measuring the center of mass of the scale value area, the center of the dial is corrected again by RANSAC fitting circle, and the pointer angle is identified by index table thinning algorithm, and finally the meter indication is calculated. The results show that this method can quickly locate the pointer meters in the gas gathering station under complex background and reduce the light interference.

1. Introduction
The gas gathering station is the key transfer station of natural gas production and transportation, which completes the throttling, separation, compression, metering and other operations of natural gas transported by each single well, and then transmits them in a centralized way. A large number of meters are needed to monitor the operation status of the system, so a large number of pointer meters are installed in the gas gathering station, as shown in Figure 1. Compared with digital meter, pointer meter has the advantages of low price, simple structure and long service life, which can better adapt to the complex working environment of gas gathering station.

![Figure 1. A large number of meters in the gas gathering station](image-url)

At present, the research of pointer meter recognition algorithm is mainly applied in the power scene. Yan Huang et al. Proposed a method composed of r-fcn (region based full convolution network), improved local threshold segmentation method and probability circle method. The experimental results
show that it still has good robustness and accuracy when the image is fuzzy, the illumination is complex or the camera angle is tilted [1]. Hao Xu et al. Proposed a new meter center calibration method, because based on the principle of energy minimization, the gray scale image has obvious gray value difference inside and outside the dial, so the center and radius information reduces the energy function to its minimum value, and makes full use of the gray scale information of the meter image, thus giving accurate calibration results [2]. Haowen Lai et al. Obtained the indication of the meter by comparing the distance between the peak value of the pointer and its nearest scale. Through the ruler search and value inference algorithm, the position and value of all rulers can be automatically obtained and inferred. The algorithm has nothing to do with any existing information in the database. The algorithm can be effectively applied to meters with equal or unequal scales [3]. Liu Y and others detected the position of the target meter based on faster r-cnn, adjusted the camera according to the detection frame, solved the problems of specular reflection and image distortion with the help of feature correspondence algorithm and perspective transformation, and obtained high-quality images. The experimental results verified the stability and accuracy of the recognition system [4].

It can be seen from the above progress that most of the researches on pointer meters get the position of the dial area in the background image through template detection and other matching methods, but it is often affected by the illumination and some other factors in the complex environment, resulting in the segmentation of the image will be biased. With the rise of deep learning technology, more and more people begin to study the application of deep learning in industry. In this paper, the deep learning network is used to extract the dial quickly in complex environment and read the indicator at the same time.

2. Quick detection of meter panel based on YOLO

2.1. Introduction to YOLO

YOLO uses convolutional neural network (CNN) to realize the graph matching image border prediction and probability calculation[5-8]. CNN is a feedforward neural network, which consists of input layer, convolution layer, pooling layer, full connection layer and output layer. Convolution layer is used to extract features, and pooling layer is used for down sampling. YOLO network consists of 24 convolution layers which are responsible for feature extraction and two fully connected layers which are responsible for predicting the position of objects and calculating the category probability. It is realized by adjusting the image size, running convolutional neural network and non maximum suppression. The YOLO network divides the input image into two parts $S \times S$. If the center of the object falls in a certain grid, the grid is responsible for detecting the object, and predicting $B$ candidate borders and the confidence score corresponding to the border, that is, the confidence score of the target object. The confidence score is expressed as:

$$ Pr(\text{Object}) \times IoU_{\text{truth}}^{\text{pred}} $$

(1)

If the candidate box contains a target, the confidence score is the IOU (intersection over union) of the candidate box and the real box, otherwise the confidence score is 0. Each candidate box has five predictive values: $x$, $y$, $w$, $h$, confidence. ($x$, $y$) and $w$, $h$ are proportional coefficients, and the value range is [0, 1]. ($x$, $y$) represents the position coordinates of the center of the candidate frame relative to the grid boundary, $w$ and $h$ are the proportion of the width and height of the candidate frame relative to the width and height of the original image. Confidence including whether the target is in the grid and the accuracy of the prediction box. For each lattice, conditional probability $Pr(\text{Class}_i | \text{Object})$ indicates the probability value of the existence of a target in the lattice and the target belongs to class $i$. Each grid only predicts the probability of a group of categories, regardless of the number and scale of prediction frames. Therefore, the network output is the tensor of $S \times S \times (B \times 5 + C)$. The structure of YOLO network is shown in Figure 2. In the test phase, we need to calculate the confidence score related to the category for each border, which is used to define the probability of the final output of each grid prediction:

$$ Pr(\text{Class}_i | \text{Object}) \times Pr(\text{Object}) \times IoU_{\text{truth}}^{\text{pred}} = Pr(\text{Class}_i) \ast IoU_{\text{truth}}^{\text{pred}} $$

(2)
YOLO network consists of 32 layers including input layer and output layer, including 24 convolution layers, 4 pooling layers and two fully connected layers. Input is 3-channel image, image size is $448 \times 448$. The activation function of Relu is as follows:

$$f(x) = \begin{cases} x, & x > 0 \\ 0.1x, & x \leq 0 \end{cases}$$  \hspace{1cm} (3)

The objective function of YOLO network in the training process is the sum of the following polynomials, $l_{ij}^{obj}$ is the j-th border in the i-th grid is responsible for relevant prediction, $l_{ij}^{noobj}$ is whether the target appears in the i-th grid. Setting $\lambda_{coord} = 5$, $\lambda_{noobj} = 0.5$ to enhance the loss of the frame coordinates of the target in the grid, and reduce the loss of confidence that the target is not included in the grid:

$$\lambda_{coord} \sum_{i=0}^{s^2} \sum_{j=0}^{B} l_{ij}^{obj} \left( (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right) + \lambda_{coord} \sum_{i=0}^{s^2} \sum_{j=0}^{B} l_{ij}^{obj} \left( \sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left( \sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2$$

$$+ \sum_{i=0}^{s^2} \sum_{j=0}^{B} l_{ij}^{obj} \left( C_i - \hat{C}_i \right)^2 + \lambda_{noobj} \sum_{i=0}^{s^2} \sum_{j=0}^{B} l_{ij}^{obj} \left( C_i - \hat{C}_i \right)^2 + \sum_{i=0}^{s^2} l_{ij}^{obj} \sum_{c \in \text{classes}} \left( p_i(c) - \hat{p}_i(c) \right)^2$$  \hspace{1cm} (4)

Figure 2. YOLO network structure

2.2. Implementation process

2.2.1. Making data sets. The data used in this paper comes from the photos taken in the gas gathering station. The data set includes 1000 original images for training and 500 images added by image enhancement methods such as image flipping and random clipping. The meter panel on the image is calibrated by using labelme software, and the label is in specific XML format, which is converted into TXT format by program. The image is randomly divided into training set and verification set, and the ratio between them is 9:1.

2.2.2. Forecast results. In this paper, the training environment is 2-way Intel CPU e5-2620 V4 @ 2.10GHz, memory capacity is 256GB; the graphics card is 3-way Titan RTX, memory is 3 * 24GB; the operating system is Ubuntu 18.04 Chinese version. The initial learning rate is $10^{-3}$. After the iteration, the data in the test set is input into the network, and the trained network weight parameters are loaded. Finally, the accuracy of the dial is 98.9% in the complex environment. Some of the test results are shown in Figure 3.
3. Meter reading recognition

3.1. Meter image preprocessing
Before reading, the image needs to be preprocessed. The preprocessing includes bilateral filtering and binarization. Bilateral filtering combines the similarity between pixel values, such as convolution kernel pixel and center pixel, and successfully removes noise while preserving image edge information. If the Gaussian filter is used, the edge will be blurred, and the bilateral filtering algorithm can effectively protect the details of the image with fast gray change between adjacent regions. For the scene of meter image recognition, the edge information of meter panel is very necessary. Therefore, this paper uses two-sided filtering algorithm for image denoising. The processing flow of bilateral filtering algorithm is as follows:

Input the image \( I \) to be filtered, and calculate the weight \( w_p \) according to the pixel value in the window \( W \) centered on the current pixel \( z \). Then the filtered image \( I_f \) is obtained:

\[
I_f(z) = \frac{1}{w_p} \sum_{z_i \in W} I(z_i) f_c(\|I(z_i) - I(z)\|) g_s(\|z_i - z\|)
\]

(5)

\[
w_p = \sum_{z_i \in W} f_c(\|I(z_i) - I(z)\|) g_s(\|z_i - z\|)
\]

(6)

After bilateral filtering, an appropriate binarization method is selected to binarize the image. The results are shown in Figure 4.

3.2. Hoffman circle detection
The basic idea of the hough circle transformation[9] is to think that every non-zero pixel on the image may be a point on a circle. Through the voting mechanism, create a cumulative coordinate plane and set a cumulative weight to find the circle. Using Hough circle detection, we can roughly detect the border around the meter, and traverse the pixels in the image to remove the noise outside the Hough circle, and only retain the dial image in the circle. The effect is shown in Figure 5.
3.3. Connected domain detection
In the binary image, the gray value is only 0 and 255, which marks the same pixels. The connected area forms a marked block. Because the gray values of different objects in the image have obvious boundaries, the objects can be marked. By using these marked areas, we can find out the contour and achieve the purpose of object segmentation. There are two common connected regions: 4-adjacency and 8-adjacency, as shown in Figure 6. According to the characteristics of scale and pointer, the area of connected domain, the centroid of connected domain and the distance between the center of circle and other conditions can be selected to extract the corresponding connected region, as shown in Figure 7 below.

![Figure 6. Connected domain diagram](image)

![Figure 7. Extract scale area and pointer](image)

3.4. RANSAC circle scale
According to the given fitting model, RANSAC[10] randomly selects samples from a pile of inlier data, calculates the fitting model parameters, and then carries out consistency detection, so as to iterate until the consistency meets certain requirements. We use RANSAC algorithm to fit the centroid position of the segmented scale line to get more accurate center and radius parameters. As shown in Figure 8 below.

![Figure 8. RANSAC fitting results](image)

3.5. Pointer refinement
Through connected domain detection, we can segment the pointer region. In order to further determine the slope direction of the pointer, we need to refine the pointer region. We use the thinning algorithm based on the index table[11]. The thinning algorithm based on index table is to traverse the edge of the
binary image, and look up the index table according to the eight connected regions of the edge point to determine whether the edge point can be deleted. According to some thinning rules, we can build an index table, so our main work is to continuously traverse the edge to determine whether to delete, until every point of the edge can no longer be refined. Predecessors have made a summary of this, and come to the conclusion that 256 cases of 8 fields around each point are put in an array of char data [256], which can't be deleted and is represented by 0, and those that can be deleted are represented by 1. Then the binary images < 0 and 1 > are obtained by image processing, and the scanned images are obtained. Y is obtained according to the formula, and data [y] is used to judge whether the point can be deleted until all the points can not be deleted. The detailed results are shown in the Figure 9.

![Figure 9. Pointer refinement](image)

3.6. Calculation of indication by angle method

Because the scale interval of the meter is uniform, combined with the range of the dial, the angle proportional relationship is used to calculate the reading. At the same time, the intercept and slope of the line where the pointer is located are obtained, and the direction of the pointer is determined. For each meter, Calculate the angle between the pointer of the meter and the 0 scale line by the slope, and then the meter indication is converted by the relationship between the range and the angle of the meter. Set the maximum scale value of the meter, that is, the range, as m, and the angle between the pointer and the 0 scale line as M, The angle between the 0 scale mark $\alpha$ and the maximum scale mark is $\beta$, Then the indicator is calculated according to the following formula:

$$X = M \times \frac{\alpha}{\beta}$$  \hspace{1cm} (7)

4. Conclusion

This paper presents a gas gathering station meter detection scheme based on deep learning and image processing algorithm. The meter panel is segmented by using YOLO algorithm to detect the input image. After preprocessing the meter image, the pointer and scale area are extracted by the connected domain segmentation algorithm. Finally, the indicator number of the meter is obtained by the angle method. The experimental results show that in the complex environment, the meter panel detection based on YOLO deep learning algorithm can still quickly detect the target position, and reduce the influence of illumination and camera angle.

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