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Accurately Localize and Recognize Instruments with Substation Inspection Robot in Complex Environments

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Abstract: This paper designs and develops an automatic detection system in the substation environment where complex and multi-inspecting objects exist. The inspection robot is able to fix and identify the objects quickly using a visual servo control system. This paper focuses on the analysis of fast lockup and recognition method of the substation instruments based on an improved Adaboost algorithm. The robot adjusts its position to the best view point and best resolution for the instrument in real-time. The dial and pointer of the instruments are detected with an improved Hough algorithm, and the angle of the pointer is converted to the corresponding readings. The experimental results indicate that the inspection robot can fix and identify the substation instruments quickly, and has a wide range of practical applications. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Inspection robot, Adaboost algorithm, Hough transform, Instrument identify.

1. Introduction

Substation is a power facility that is mainly used for voltage conversion, power acceptance and distribution in power system. Substation inspection is a necessary step to sustain its normal running, which mainly covers the inspection of instruments, switches, disconnectors and heating equipments. The current "four remotes" (remote viewing, remote signaling, remote control, remote adjustment) applied in substation can only control the substation video surveillance, without the ability to analyze the operating status of the target device, leaving potential safety hazards in substation operation.

Zhou et al described the development and application of intelligent substation inspection robots, and pointed out that instrument recognition is an important function of the substation inspection robots [1]. However, he didn't discuss how to research and design. Wen et al proposed an approach to precisely interpret the dial instruments based on computer vision. But this method obtains high precision only in the case that the camera is relatively fixed and the position of the instrument in the image is pre-determined [2]. A dominant color extraction method was proposed by Sun et al [3], which is quite robust against illumination changes in scenes. It ensured the color features of objects can be extracted successfully. But, it's difficult to get the precise results when a target is far away and the target image is quite small in size. Thus, the above instrument recognition methods can't be directly applied to identify the instrument reports in inspection robots under complex environments [4]. The factors mainly include: whether mobile camera can precisely fix the position of the target, the size of the acquired targets, etc.

This paper presents a method for inspection robot to precisely fix and identify the instruments reports in the complex environment of the substation during its move. The substation inspection robot is equipped with high-definition CCD (Charge-coupled Device) camera of 360 degrees horizontal and 90 degrees vertical view, and an infrared thermal imager. The robot can navigate along the planned route with multi-angle, wide range inspection, and visual servo can effectively track targets and classify instruments within the substation in complex environments. Then it can identify and read out the instrument report in real-time, transmit the analysis results through a wireless network to the remote control center, thus the substation can be automatically inspected without human observer. This paper achieves certain breakthrough in fast-tracking and analyzing targets using visual servo.

2. Fast-tracking of Inspection Targets

2.1. Inspection Routine

Inspection routine of robots in the substation simulates the inspection process of human inspector. Substation inspection robots first obtain the target position, adjust the target image to the optimum position, then identify the target and get the target data.

2.2. Instrument Identification Algorithms

In a complex environment like substation, inspection robots should first fix the targets to identify instruments. AdaBoost (adaptive boosting) algorithm is a learning algorithm to improve the accuracy of a given method, and is a practical algorithm based on weak learning theorem. AdaBoost algorithm has been successfully applied in many fields [5].

AdaBoost algorithm is based on a given training set(x1, y1), …, (xm, ym), where xi belongs to a case space X, M∈{-1, +1}. For initialization, Adaboost specifies the distribution of training set as 1/m, and calls weak learner to train the training set according to the distribution. After each training, Adaboost updates the distribution of training set based on the training results, and iteratively trains T rounds according to the new distribution. Finally it would obtain an estimate sequence h_l, …, h_t, each with a certain weight. And the final estimate H is obtained by weighted voting.

$$f(x) = \sum_t a_t h_t(x)\,, \qquad (1)$$

The final classification rules of AdaBoost algorithm is theoretically derived by Schapire, Singer and Freund from:

$$H(x) = sign(f(x))\,, \qquad (2)$$

The error margin is:

$$\frac{1}{m}\left|\{i : H(x_i) \neq y_i\}\right| \leq \frac{1}{m}\sum_i \exp(-y_i f(x)) = \prod_i Z_t\,, \qquad (3)$$

In (3), the training error decreases rapidly by minimizing Z_t through carefully selecting a_t and h_t in each round. Schapire and Singer modified the original Adaboost algorithm, extending estimates range from {-1, +1} to [-1, +1]. That is, they replaced the original two-valued function with real function, and discussed how to select a_t and h_t in such a case. The improved algorithm, where the sign of h_t is regarded as the predicted class, and the absolute value of h_t as the confidence level of prediction, is also known as the real AdaBoost algorithm.

This paper utilizes HAAR-like feature to extract the characteristics of the instrument with Adaboost learning algorithm. Due to the variety of instruments, it is necessary to establish the corresponding feature library for each type of instrument, which necessitates the collection of a large number of non-identical samples. After sample collection, numerous positive samples should be included in the training set of the classifier, and then calculated using the Adaboost algorithm. Finally, the data file containing the instrument feature is obtained [6], based on which the target in the image can be calculated in the identification process. The objective function is:

$$\sum_{i=1}^{N} \exp(y_t H(x_t))\,, \qquad (4)$$

$$y_t \cdot H_t(x_t) :\to \{-1,+1\}\,, \qquad (1)$$

Adaboost identifies the instrument, obtains meter area, and then read the meter pointer. Extensive experiments showed that with appropriate target size, desired accuracy can be achieved by combining instrument recognition algorithms and pointer recognition algorithms.

2.3. Localize Accurately the Target

Recognition accuracy heavily relies on image resolution, the higher the resolution, and the more accurate the reading. Only when the resolution of the instrument panel reaches a certain upper bound, can the reading accuracy be ensured. Table 1 shows the influence of resolution on reading accuracy of different instrument panels.

Table 1. The resolution on the meter reading accuracy rate.

No.	60*60	120*120	180*180	240*240	300*300
1	0.09	0.21	0.88	0.98	0.99
2	0.15	0.51	0.91	1.00	1.00
3	0.08	0.35	0.98	0.99	1.00
4	0.00	0.13	0.91	0.95	0.98
5	0.23	0.29	0.89	0.98	0.99
6	0.00	0.34	0.94	0.95	0.98
7	0.00	0.32	0.9	0.96	0.99

As can be seen from Table 1, for different instruments, in order to achieve satisfactory accuracy, image resolution should be not lower than 300×300. Owing to the innate position error of the robots, how to control the camera, zoom in, and ensure that the target is not lost after moving to the observing position is the key to accurately localize the target.

2.4. Improved Target Positioning Algorithm

Traditional target positioning algorithms obtain appropriate target size through detecting the position and size of the target in real-time, and adjusting position of PTZ (Pan/Tilt/Zoom) and camera focus. The shortcomings of traditional positioning algorithm are:

1) Time-consuming, mainly due to the high frequency of the target;

2) Target missing, without prediction whether the target would be lost.

During the robot inspection, because of the numerous targets, the time requirement is quite demanding. Target missing will cause re-inspection by robot or an alarm to incur manual inspection, leading to waste of time and damage of robot's practicality.

The target positioning algorithm proposed in this paper firstly identify inspection targets, obtain the target position and target size, and then transform the image recognition parameters into control information based on optical principles. Control information includes PTZ horizontal rotation angle θx, vertical rotation angle θy, and focal length f. Entire visual controller can be expressed with a few functions

$$(x, y, w) = R(image), \quad (6)$$

where image is the input sample image, R is the identification function, the output (x, y) is the center of the target, and w is the target size.

$$(\theta_x, \theta_y, f) = g(x, y, w), \quad (7)$$

where g is the function to transform the parameters in the image into the PTZ parameters θx, θy and camera focal length parameter f.

Image recognition helps to obtain specific information about the target inspection, but it can not be directly used to adjust the camera. Optical imaging technology is needed to convert the information to robot PTZ and camera focal length control information.

Assuming the output target image identification information is (x, y, w), then the offset of target and the center of the image is calculated as:

$$(x0, y0) = (x - W|2, y - H|2), \quad (8)$$

where W and H stand for the length and width of the image. Next the relationship between offset and PTZ rotation angle is calculated.

Now to calculate angle θ of the target offset center, according to the geometric relation,

$$\tan\theta = \overline{O2, y2} / \overline{O, O2}, \quad (9)$$

Since the distance between (O, O2), Eq. (9) can't be directly used to get θ. Even if the distance of every target is measured, the measurement accuracy can't be ensured due to the variety of the devices in substation, not to mention that many devices are high-voltage equipment. Even with accurate measurement, this algorithm lacks flexibility since additional inspection equipment leads to additional accurate measurement between observation point and the target. Well, another geometric relationship,

$$\tan\theta = \overline{O1, y1} / \overline{O, O1}, \quad (10)$$

where (O, O1) is focal length f. With known camera magnification zoom and above given camera parameters, the relationship between focus and magnification can be calculated:

$$f = zoom \times 4.7, \quad (11)$$

(O2, y) is the distance between the target and the CCD center in the direction Y, and the implicit relationship between it and the target position in the image is:

$$y_1 / h = y / H, \quad (12)$$

With h as the CCD height and H as the image height, (13) can be calculated:

$$than(\theta) = y \times h / H \times Zoom \times 4.7, \quad (13)$$

where θ is the PTZ vertical rotation angle, and PTZ horizontal rotation angle can be calculated similarly.

Thus (θx, θy) can be got, enables the inspection target to move image center. When the target size w is less than the desired target size W, the target size needs to be magnified. And the magnification is:

$$w/W = f/F\,, \tag{14}$$

where F is the desired focus, f is the current focus, and the magnification of the camera can be got:

$$zoom = f \times W/(w \times 4.7)\,, \tag{15}$$

Formula (5) has been successfully converted by now. Vision controller will output control information to manipulate the robot and adjust its gesture in order to fix the inspection target and keep it in the image center. The error is only related to PTZ angle error. PTZ angle information helps to position robot to the present location and to adjust the camera focus to wide-angle, guaranteeing a wide enough view.

The process is coincident with human observation process. In principle, the clearer images obtained by vision servo, the easier the subsequent image processing method for reading instrument, and the higher the accuracy can be got. Assuming the distance between the original position and the final position can be expressed as $d2 = \sqrt{(x2-a)^2 + (y2-b)^2}$, then the time consumed by the two methods with the same distance d is shown in Fig. 1.

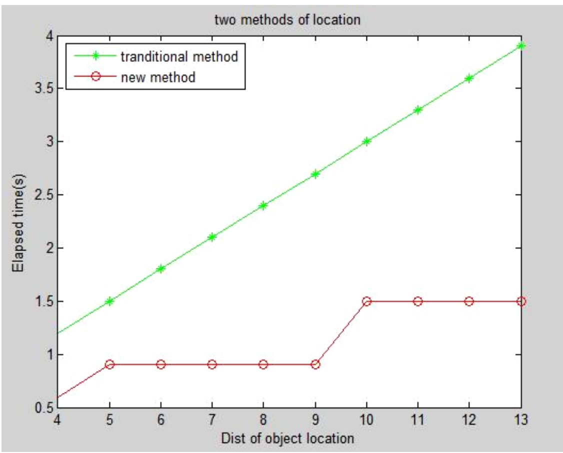


Fig. 1. Comparison of consumed time.

3. Target Analysis and Identification Method

3.1. Key to Instrument Analysis

Current research on instrument reading in China mainly focuses on fixed-point monitoring applications, and there exist various methods for instrument interpretation [7]. Fixed-point monitoring is relatively easy, since the dial is in a fixed position in the image, the position of the pointer would be enough to read the instrument report. For instrument without fixed-point, the following issues should be addressed to recognize and read the instrument:

1) How to identify the dial in complex environments;

2) How to obtain the appropriate size of the instrument;

3) How to select the meter reading methods.

For an instrument with fix-points, only problem (3) needs to be solved. For instruments without fixed-points, problem (1) and (2) should be solved first to extract the target image from a complex environment, and convert non-fixed point problem to fixed-point like problem. Therefore, processing instruments without fixed-points requires more complex algorithms.

3.2. Instrument Reading Method

In fixed-point instrument recognition algorithms, if tiny scale lines can not be correctly identified, it is impossible to correctly identify the instrument data. The paper addresses this problem with the following methods:

1) A new algorithm is proposed: first to refine the pointer, detect the pointer as a straight line, and then determine the rotation angle of rotation of the pointer to identify the instrument image;

2) Hough circle detection method is improved: to obtain dial circle and center;

3) By means of hough to detect pointer, with additional information such as the center of the dial, to filter out the interfering lines and accurately identify the pointer.

To detect the center of the dial and pointer, preprocessing of the image is a necessity. Fig. 2 shows the pre-processing of the image.

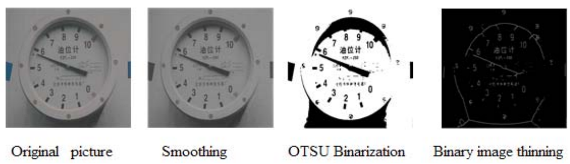


Fig. 2. Preprocess.

The image preprocessing employs classical image processing algorithms to obtain detailed images. Image binarization will directly affect the result, and 0tsu's "Otsu Law" is a widely applied threshold selection method due to its simplicity and clear physical significance [8].

3.3. Dial Pointer Detection

Refined image will be obtained after image preprocessing, then Hough transformation is utilized to detect the pointer. Hough transform is to transform image from spatial domain into parameter domain. Taking Hough line transformation as an example, the linear function expression in two-dimensional Cartesian coordinate system is:

$$y = f(x) = a * x + b\,, \tag{16}$$

Polar coordinates function can be expressed as:

$$y = \rho * \sin\theta\,, \tag{17}$$

$$x = \rho * \cos\theta\,, \tag{18}$$

The conversion process from two-dimensional space to linear parameter is as follows: scan from im (1,1) to im (m, n) in the oil level gauge refinement map; if im (i, j) is 1, the for θ from value 0 to 360, there is a corresponding ρ, generating a two-dimensional parameter space. For the same straight line, (θ, ρ) will remain the same. So the accumulator A (θ, ρ) records the number of pixels of the same line. By analyzing the data accumulator array A, and with threshold value, lines in the two-dimensional space can be detected [9].

During the entire transformation, the time and space complexity cost from two-dimensional space to the parameter space conversion is quite high. For two parameter space conversion, this time and space overhead is reasonable. While for three-dimensional parameter space, the time and space overhead is too much for a real-time response.

A circle requires three parameters to determine its expression:

$$(x - a)^2 + (y - a)^2 = r^2\,, \tag{19}$$

Polar coordinates function can be expressed as:

$$y = a + r * \sin\theta\,, \tag{20}$$

$$x = a + r * \cos\theta\,, \tag{21}$$

The traditional hough transform DHT can not meet the needs of real-time processing. Improved GDT circle detection algorithm can reduce three parameters to two parameters, however, without a definite radius R, parameter space transformation can't be determined either [10].

This paper proposes a new algorithm: firstly we calculate the coordinates of the center, and then determine the unknown parameters R. After that, it is easy to detect the desired circle by image scanning. This novel center calculation algorithm is: we divide the circle edge into N sections, draw the perpendicular bisectors of the N segments respectively, whose intersection indicates the position of the circle center. The time complexity of the algorithm is greatly reduced, since only a two-dimensional array with the same size is needed to store the intersection points, and the center position can be easily obtained by calculating the number of intersections. After this, the circle detection will be relatively easy.

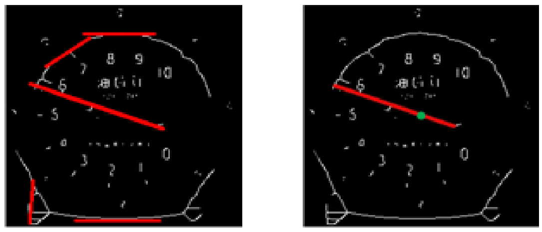
$$d = |Ax + By + C| / \sqrt{A * A + B * B}\,, \tag{22}$$

The algorithm adjusts the relevant parameters to obtain the center coordinates of curves, and is very helpful to identify the instrument. After calculation of center coordinates, pointer line can also be obtained with Hough line detection. The pointer can be identified if it is relatively longer than the other lines. However, in practice, the interference is unavoidable, resulting in non-pointer lines. This interference can be excluded by calculating the distance between the line and the center:

$$d1 = \sqrt{(x1 - a)^2 + (y1 - b)^2}\,, \tag{23}$$

$$d2 = \sqrt{(x2 - a)^2 + (y2 - b)^2}\,, \tag{24}$$

Fig. 3 demonstrates the pointer detection results with and without additional condition.



additional condition. without additional condition

Fig. 3. Comparison of two line detection methods.

Experiments demonstrated that with additional parameters like center detection and the parameters of the pointer itself, interference can be filtered and pointer detection error can be avoided. If the location and size of the dial can be determined, dial reading can be achieved. When the instrument resolution is high enough, accurate instrument readings can be obtained. In fact, using the above described positioning algorithm, as long as the parameters of the target size is preset, the desired target image can be got with computer vision algorithm, and after analyzing, accurate results are obtained.

4. Field Application

The algorithm in this paper was validated with a substation inspection robot (see Fig. 4) in a 220 kV substation, Mengdu, Hunan. Six different randomly selected instruments were tested for identification. Fig. 4 illustrates the field application.

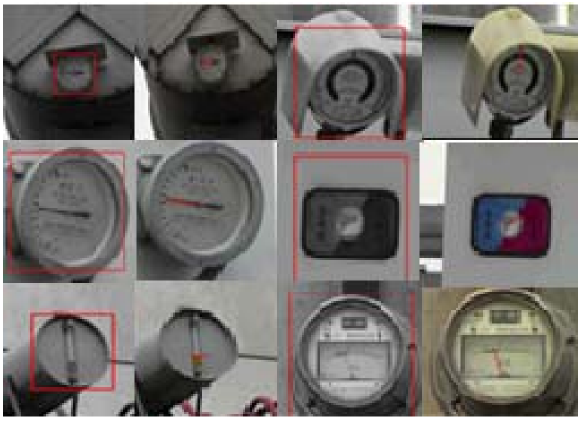


Fig. 4. Application site.

For the randomly selected instruments, after 120 tests in one week, the identification results are compared with the standard value stored in system pms, as listed in Table 2.

Table 2. Experiment test result.

No.	Recognition	Identification	Standard	Error
1	99.00 %	5.146	5	2.92 %
2	97.83 %	4.862	5	2.76 %
3	98.50 %	0.341	0.35	2.57 %
4	97.18 %	4.067	4	1.68 %
5	99.4 %	1	1	0
6	98.25 %	0.486	0.5	2.8 %

As can be seen from Table 2, we achieved a recognition accuracy of 97 % in the complex environment of substation, recognition error is less than 3 %, which meets the requirements of substation equipment inspection. The current manual inspection can only determine the approximated meter data due to lack of qualification and experience.

5. Conclusion

This paper effectively solves the target tracking and analysis problem under complex environment in a substation. This is also the first try in instrumental identification algorithm in Chinese substations, which provides a way to achieve autonomous substation inspection. Since most of the substations are outdoor, which are highly influenced by the weather and environmental changes, our future work includes algorithm adaption, image resolution requirements and the accuracy of the instrument readings, and extensions of the algorithm into other applications.

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