A Robot Indoor Position and Orientation Method based on 2D Barcode Landmark

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***Abstract*—A method for robot indoor automatic positioning and orientating based on two-dimensional (2D) barcode landmark is proposed. By using the scheme of the 2D barcode for reference, a special landmark is designed which is convenient to operate and easy to recognize, contain coordinates of their absolute positions and have some ability to automatically correct errors. Landmarks are placed over the "ceiling" and photographed by a camera mounted on the robot with its optical axis vertical to the ceiling plane. The coordinates and angle of the landmark is acquired through image segmentation, contour extracting, characteristic curves matching and landmark properties identifying, and then the robot's current absolute position and heading angle is computed. The experiments proved the effectiveness of the method and shows that the method can meet accuracy requirements of indoor position and orientation.**

***Index Terms*—indoor positioning and orientating, landmark, ceiling, computer vision, two-dimension barcode**

I. INTRODUCTION

The subject of robot indoor automatic positioning and orientating represents an important research direction. Since satellite signals suffer screening indoors, satellite-based positioning techniques like GPS cannot give full play to their quick and precise location. Instead, the indoor location in a wireless network serves now as a hot approach. However, it achieves node positioning typically via one node relative to another based on chain circuit quality index or received signal strength except the poor accuracy of positioning with error arriving at as much as 25% and hence this locating technique fails to reach the requirement[1]. As image processing techniques are progressing, the landmark-based robot vision navigation method finds its widespread applications. For example, with the help of mixed codes as landmark over the ceiling, a location method is proposed in [2], where the landmark which is labeled with serial number and direction-asymmetrical channels is used to help recognize 360° heading angles. Reference [3] and Reference [4] proposed a method of the panoramic vision-based robot autonomous locating. From the omni-directional images of the environment photographed by panoramic camera on the robot, the landmarks on the ceiling are identified, followed by determining the current coordinates of the robot through a triangular location method. Reference [5] developed a positioning approach which combines the RFID with computer vision technique. In such a way, the indoor environment is denoted by a node tree, of which each node comprises an ID tag and a color card and act as a landmark stuck onto the ceiling. With the ID tag recognized by the RFID and the location and direction of the landmark, the robot is located in an accurate manner. Reference [6] developed a scheme for a small-sized robot as a cleaner, with the positioning based on the 2D barcode stuck onto ground containing the information about its absolute position as a landmark. The landmark is visible only under an ultraviolet lamp, and the distance between the robot and landmark is determined by the infrared ranging module.

According to characteristics of the robot navigation indoors, a method for indoor positioning and orientating based on the 2D barcode landmark is proposed. The special 2D barcode landmarks have ability of self-correcting error and are stuck over the ceiling plane according the coordinates which they contain. The ceiling images are captured by the robot camera in its journey. The camera's optical axis is vertical to the ceiling plane. Through image preprocessing and landmark recognizing, we can locate the landmark, get the information contained in the landmark, and obtain the coordinates of the robot's current absolute position and the heading angle. Our method is featured by 1) a ceiling plane that is relatively open and background-simple is used as a space for landmarks, thus allowing to decrease screening and noise interference; 2) robustness and certain capability to correct error; 3) being easy to expand the robot positioning into a larger environment; 4) simple procedure for image processing. Compared to Reference [6] which exploits the similar method, the advantage of the proposed approach include：1) The barcode give the absolute location of robot, so lower the complexity of location algorithm. 2) The barcode designed is relative simple so that the image process is simple. 3) The landmarks stuck in the ceiling can be avoided to be destroyed in real environment.

II. LANDMARK DESIGN AND RECOGNITION

Because of the landmarks stuck on the ceiling, the optical axis of the camera is required to be approximately

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vertical to the ceiling plane to make a roughly similarity transformation between the image landmark and its real pattern, thereby decreasing image distortion effectively for subsequent treatment.

A. Landmark Design

The structure of presented landmark is shown in Fig.1.

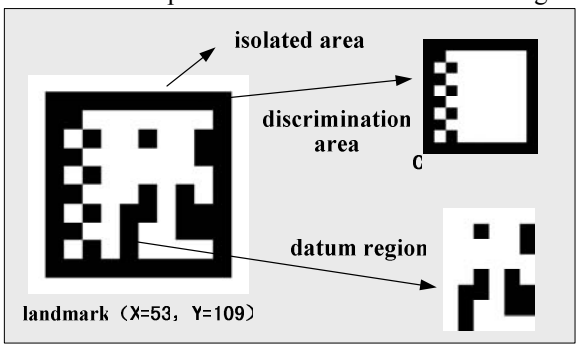


Figure.1. a schematic diagram of landmark's structure.

The form of landmark is a square composed mainly of sub-squares of strong color contrast and in the paper the colors are black and white, with the black (white) subs-square denoting "1" ("0") in the binary system. The landmark consists of an isolated area, a discrimination zone and a datum region. These zones are explained as follows.

1) There is an annular space full of white subs-square called isolated area, which will help extract the landmark zone in image segmentation.

2）The discrimination area has its roles in ① judging whether a particular connected domain is the landmark area and ② showing the data reading rule in the datum area. For instance, when the discrimination zone is in the place of Fig 1 (the original point C of the zone being at the bottom left corner thereof), the data reading is performed from bottom to top and from left to right.

3) The datum zone is composed of a number of white and black sub-squares. Since a small quantity of information is contained in the landmark we split the data zone into 8×6 and adopt the direct access mode, i.e., the data denotes actual information rather than the index of the actual information. To improve the robustness of landmark recognition, the data can be encoded by means of self correcting method. Although some self correcting method (e.g., QR code) are able to detect and correct any wrong bit of a data，they have shortcomings including complex algorithm, poor real-time character, and especially greatly raising the data length which lead to the increasing of the number of sub-squares, thus increasing the difficulty in image processing[7][8]. Taking all together, we encode data with Hamming code. It is possible to correct single-bit error, thus balancing the real time character and error correction. After encoding, extra 4 bits are added to a byte data, so the 8×6 pieces of sub-squares can represent 4 bytes data (8×6÷(8+4)=4). In our work the landmark contains only information on the X and Y coordinates and each is denoted by 2 byte, so that it can denote 65536×65536 places, suggesting its good expansion.

B. Landmark Recognition

To overcome the disturbance caused by vent etc. and achieve good recognition, the landmark should be made by use of material that is in sharp contrast in color to the ceiling (such as red and blue) and the basic idea behind the landmark recognition is to utilize different diffusion principles for diverse colors to segment the threshold value of an image [2] to get a binary image, followed by seeking the connected domain containing the landmark information, and extracting them from which. In the following we expound the key steps of searching the connected domain, extracting information on the closed contour, and discriminating the landmark shape and content.

(1) Connected Domain Searching and Contour Extraction

Presented is an algorithm for detecting the connected domain based on searching the neighboring zones, and it makes use of the algorithm of regional growth idea, avoiding repeated marking and thus good result is achieved.

1) Image scanning is performed to search for an unmarked black pixel (assuming the black pixel to represent the target pixel) and if not found, then the procedure is stopped. The unmarked pixel is put into a FIFO buffer for later processing and it is marked to denote that it has been examined.

2) A pixel is taken out of the FIFO buffer, followed by judging whether there are unmarked black pixels in its 5×5 neighbors. If existed, we put the unmarked black pixel into the FIFO buffer and marked. Otherwise we leave it alone.

3) All pixels in the FIFO buffer are examined using the step 2), till the FIFO buffer is empty. It is shown that we have found a connected domain, followed by recording information about the connected domain size, maximum and minimum row and column numbers.

4) The area threshold is utilized (which is determined according to used camera and experiments). The area of the connected domain, when smaller than the threshold, is considered to be noise and at this time we carry out step 6). Otherwise we go on to the next step.

5) Gain the contour of the connected domain above. (Single-pixel width).

6) The same procedure (steps 1 to 5) is repeated for the next connected domain.

The algorithm is able to detect all connected domains by scanning once, showing its high efficiency, and this method suffers no effect of the shape and number of the connected domains, indicative of high robustness.

(2) Discrimination of extracted landmark information

After gaining each connected domain and its outline in the image it is needed to judge whether it is the landmark region. To improve the reliability of recognition, both the shape and the content of a landmark are discriminated.

The landmark shape is discriminated at first. As stated earlier, there is a roughly similarity transformation between the landmark image and its real pattern, so that landmark shape in the image is similar to a square. Accordingly, the shape characteristic curve constructed

thereby is used to discriminate the landmark shape. As shown in Fig.2, we assume I_S to denote the contour of a connected domain to be discriminated, with the detailed procedure as follows.

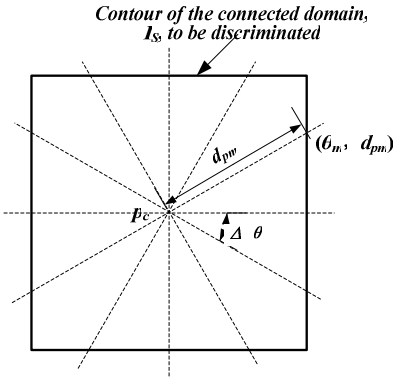


Figure.2. Schematic diagram of toroidal equispaced sampling

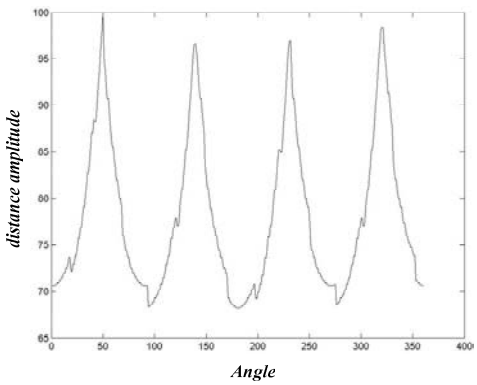


Figure.3. Schematic diagram of shape characteristic curve

1) To calculate the centroid p_c of the connected domain contour Is;

2) As shown in Fig.2, toroidal equispaced sampling is made in I_S with p_c as the original point of the coordinates [9]. The number of sampling points is given by N_θ and the sampling is made at intervals of $\Delta\theta$ ($\Delta\theta=2\pi/N_\theta$), thereby leading to the shape characteristic curve. And the curve takes the angle θ_m as the abscissa and the distance d_{pm} as the ordinate, in which $\theta_m=(m+1)\ \Delta\theta$, with m=0.. N_θ–1, and d_{pm} denotes the distance between the sampling point of I_S at the angle of θ_m and the centroid p_c. Fig.3 depicts a shape characteristic curve of a landmark from an experiment.

3) The shape characteristic curve of I_S is normalized, which is compared with the normalized shape characteristic curve of a standard square to calculate the error (denoted as e) between them. When the error e is larger than the threshold value ε_0 (which can be set to be larger because of the content discrimination subsequently, and in our experiment ε_0 is set to be N_θ/100), we consider that I_S is not in conformity with the landmark shape, and in this case we stop the operation. Otherwise the next step is implemented;

4) Four straight lines denoted as l_{11}, l_{12}, l_{21} and l_{22} are extracted from I_S by means of the Hough algorithm with the related angles (amplitudes) of being $l_{\theta 11}$, $l_{\theta 12}$, $l_{\theta 21}$ and $l_{\theta 22}$ (l_{A11}, l_{A12}, l_{A21} and l_{A22}), and are separated into two groups, according to the relation between angle and amplitude. They should satisfy the following conditions: ① $|l_{\theta 11}-l_{\theta 12}|<\varepsilon_1$ and $|l_{\theta 21}-l_{\theta 22}|<\varepsilon_1$, ② $|\ l_{\theta 11}-l_{\theta 21}-90|<\varepsilon_2$ and $|\ l_{\theta 11}-l_{\theta 22}-90|<\varepsilon_2$ and $|\ l_{\theta 12}-l_{\theta 21}-90|<\varepsilon_2$ and $|\ l_{\theta 12}-l_{\theta 22}-90|<\varepsilon_2$, ③ $\|\ l_{A11}-l_{A12}|-|\ l_{A21}-l_{A22}\|<\varepsilon_3$, in each of which ε_1、ε_2 and ε_3 are the threshold and taken as 10, 20 and 15, respectively in our experiments.

It is worth noting that if the approximate verticality assumption cannot be satisfied, the similarity transformation between the landmark image and its real pattern is false. To deal this, the threshold ε_0, ε_1, ε_2, ε_3 should be raised a bit to use the landmark content discrimination to judge in next step.

Next, we discriminate the landmark content exploiting the discrimination zone, the discriminating steps shown below.

1) Based on the landmark structure, two groups of lines are obtained from step above, with which to generate 9 new lines for each in accordance with a certain algorithm (see Fig.4). Assuming the lines l_{11}, l_{12}, l_{21} and l_{22} to have the slope (intercept) of ka_{11}, ka_{12}, ka_{21} and ka_{22} (ba_{11}, ba_{12}, ba_{21} and ba_{22}) to be, we obtain the slope k_{ji} and intercept b_{ji} of the newly-generated lines l^1_i (i=1…11) and l^2_i(i=1...11), as given below (Note that in the group of new lines, $l^1_1= l_{11}$, $l^1_{11}= l_{12}$, $l^2_1= l_{21}$ and $l^2_{11}= l_{22}$).

$$\begin{cases} k_{ji} = \dfrac{ka_{j2}-ka_{j1}}{10} i + \dfrac{11ka_{j1}-ka_{j2}}{10} \\ b_{ji} = \dfrac{ba_{j2}-ba_{j1}}{10} i + \dfrac{11ba_{j1}-ba_{j2}}{10} \end{cases} \quad (1)$$

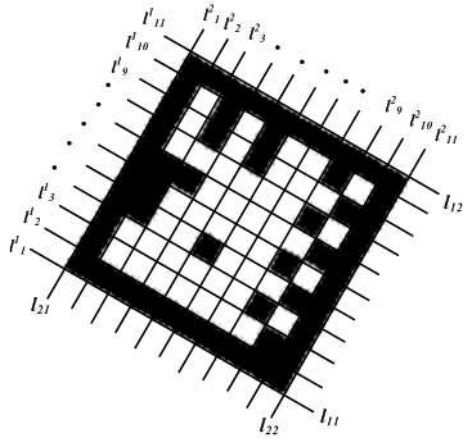


Figure.4. A schematic diagram of generated lines

2) The connected domain to be discriminated is divided into 10×10 sub-squares (10 rows and 10 columns) using l^1_i and l^2_i, followed by calculating the vertexe coordinates of each sub-square. Set a sub-square to be in row m and column n then the coordinates of the four vertexes can be calculated by the intersections of lines l^1_m and l^1_{m+1} with l^2_n and l^2_{n+1}.

3) The 100 sub-squares are transformed into 10×10 two-dimension array designated by A, and then calculate the array value $A[m,n]$. Firstly the center of each sub-square is acquired by its four vertexes. Secondly, assuming the width and height of the sub-square is w_s and h_s respectively, we calculate the number N_t of black pixel

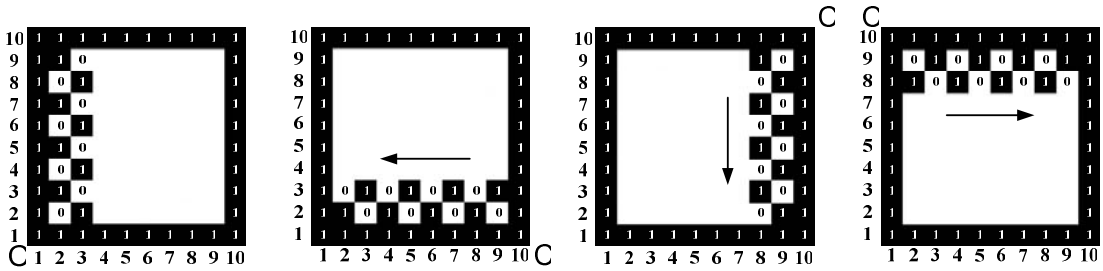


Figure.5. Four patterns of the landmark

within the center area of $(w_s/2+1) \times (h_s/2+1)$. Finally, if N_t / $((w_s/2+1)\times(h_s/2+1)) \geqslant 70\%$, we have $A[m,n]=1$, and otherwise $A[m,n]= 0$.

4) According to the characteristics of landmark discrimination domain, the outermost layer is black. It needs to judge if the 2D array A in row 1_{th}, column 1_{th}, row 10_{th} and column 10_{th} (totaling 36 elements) are equal to "1" (see Fig.1), and if so, we carry out the subsequent steps, and otherwise it indicates that the connected domain is not the landmark domain.

5) Following the landmark features, no matter how many degrees the image landmark rotates through, the landmark can finally be transformed into the four patterns shown in Fig.5, where the digits outside the landmark represent the subscript of the 2D array A, the digits inside the landmark represent the value of the 2D array A and the arrows mark denote the direction the data are read. Therefore, the 2D array A elements in two columns [rows] headed by (2, 1) and (3, 1) [(10, 2) and (10, 3)] and also (9, 10) and (8, 10) [(1, 9) and (1, 8)] are judged to see whether they satisfy the digital sequence of 1010101011 and 1101010101 separately. If one of the cases is met, then the connected domain is considered to be the landmark region and meanwhile get the original point C of the discrimination domain and the reading rule. Otherwise, it is not the landmark region.

Following the steps above, the information on the landmark coordinates is acquired on the basis of the C-dependent data reading rule.

III. Robot Location Estimation

Based upon landmark identification and coordinates extraction, we can find the absolute coordinates of the robot in the environment. Fig. 6 is the schematic diagram of the robot location estimation in 2D. In Fig. 6 point B designates the image center, point A is the landmark center and XAY coordinates denote the coordinate system of the landmark. The image plane of the robot-mounted camera has its column direction acting as the direction it moves, so that the direction of the robot moving is actually parallel with the column orientation of the image.

Following the landmark design principle, the coordinate the landmark contains are actually the global position of the landmark's center so that we can get the global location of the robot if the relative position of the robot to the landmark is gained.

Assume in XAY system, with $|AB|$ being the mode of vector AB, i.e., the distance between A and B, α being the included angle between the X axis and the row orientation of the image (also known as the heading angle of the robot movement), β being the included angle between vector AB and the column orientation of the image and θ being the included angle between vector AB and landmark X axis. Then following the geometry of Fig.6, we obtain the coordinates of image central point B (in units of pixels) in the XAY system of the landmark. We thus have

$$\begin{cases} x_B = |AB|\cos\theta = |AB|\cos(\beta-\alpha) \\ y_B = |AB|\sin\theta = |AB|\sin(\beta-\alpha) \end{cases} \tag{2}$$

Assuming the global coordinates of the landmark to be (X_1, Y_1) we have the global coordinates of the robot to be (X_2, Y_2)

$$\begin{cases} X_2 = X_1 + Sx_B = X_1 + S|AB|\cos(\beta-\alpha) \\ Y_2 = Y_1 + Sy_B = Y_1 + S|AB|\sin(\beta-\alpha) \end{cases} \tag{3}$$

Where $|AB|$, α, β and θ are acquired via image processing in the landmark recognition step, and the variable S is the proportional factor that can be found either by in-advance camera calibration or by real-time calculation of the side length M of the landmark image and the side length of the actual landmark.

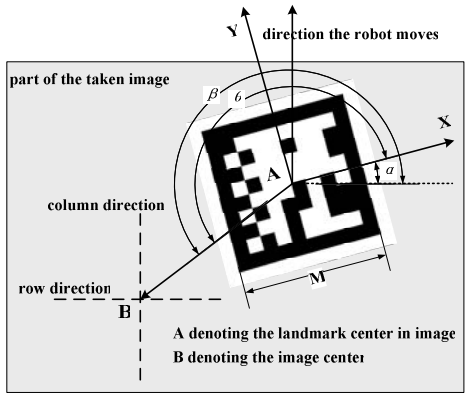
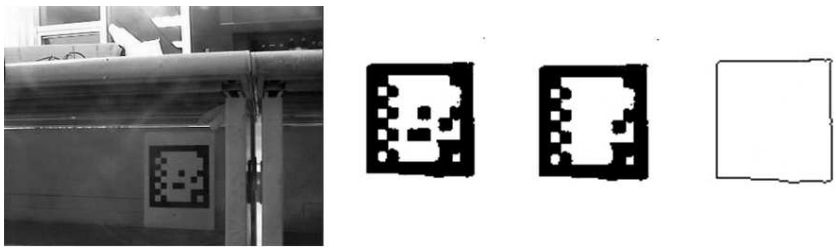


Figure.6. A schematic diagram of the robot location estimation in 2D

When more than two landmarks are measured at the same time, multiple estimates of the robot position (VX_i, VY_i, with i = 1, 2, …, n) can be found. Even if the camera is calibrated, slight distortion remains possible and the farther the point away from the image center, the greater this distortion. Hence, a weighed averaging is adopted to improve positioning accuracy in order to get the final estimate of the robot location (X_2, Y_2) through



(a) (b) (c) (d)

Figure.7. Part of the treated images in an experiment, with the origin image in a), the binary image of landmark in b), the landmark zone after the searching in the connected domain in c) and the contour of the landmark zone in d)

TABLE.I
Repeatability of experimental data of static positioning

	1	2	3	4	5	6	7	8	9	10	standard deviation
X-axis (mm)	187.2	187.4	187.3	187.2	187.3	187.1	187.3	187.4	187.3	187.3	0.087
Y-axis (mm)	214.6	214.3	214.3	214.7	214.6	214.4	214.6	214.3	214.4	214.6	0.147
heading (°)	36.7	36.7	36.6	36.6	36.7	36.7	36.8	36.6	36.6	36.7	0.064

$$X_2 = \sum_{i=1}^{n} \omega_i VX_i \quad Y_2 = \sum_{i=1}^{n} \omega_i VY_i \quad \omega_i = 1 - \|d_i\| / d_{\max} \tag{4}$$

in which d_i is the distance between the i-th landmark and the image center, ω_i is the weighed value of normalized distance and d_{max} is the maximal distance. Thus, the landmark closer to the image center makes greater contribution to the estimated robot position vice versa.

A special case should be considered. The landmark recognition of an image fails somehow and in this case we can add some predictive algorithms (e.g., Kalman filter algorithm) to the calculation, which is responsible for prognostic tracking of the robot's current location, thus resulting in higher robustness of the system.

IV. Experiments and Analysis

To test the effectiveness of the presented method, experimental approaches are used for emulation by means of video simulation. In experiments the image capturing system consists of the SONY FCB-EX980 camera with 16mm Len and QP300 image acquisition card. The image resolution is 720×576. And the computer has Intel E2200 CPU and 2G DDR2 memory, with the algorithm realized by the C++ language and the compiling program of VisualC++6.0 in WinXP system. Fig.7 depicts the intermediate results of algorithm treatment in an experiment.

1) Experiment on Static Landmark Positioning

The static location experiment is conducted in a real environment. The landmarks are put in a scenario similar to the "ceiling" to allow us to make static landmark positioning by the photographed landmark image with the aim at testing the positioning repeatability when the camera is fixed in location. Table I gives the data from an experiment, showing the repeatability of algorithm with high accuracy.

Besides, such experiments are made to validate the effectiveness and reliability of landmark recognition in a variety of cases, with the focal lengths of 8 and 16mm, the acting distances of 5, 8 and 10m and the landmark sizes of 300mm×300mm, 500mm×500mm and 800mm×800mm. Based on multiple runs we discover that: ① the difficulty in processing image is decreased remarkably when the field of view of the camera contains 1 ~ 2 landmarks, thereby increasing the rate of success and dependability of recognition. ② Lens with short focus (such as 8mm) and landmark with small size (such as 300mm×300mm) will make the sub-squares smaller in size (in pixel unit), so that the result is easy to affect by noise and decrease the recognition rate. So it is necessary to choose the lens with appropriate focus and the landmark of proper size, and make the size of sub-squares in image large as possible as.

2) Emulation Experiment on Robot Dynamic Positioning and Orientating

With the video files of simulated straight movement and revolving motion of the robot as the input for the algorithm, the emulation experiments are conducted with the positioning and orientating in a dynamic manner. The straight and revolving movements each produce five groups of emulation video files, where the landmark size is 400mm×400mm and the proportional divisor S is 2. The experiments are as follows.

① Experiment 1: The robot moves along a row or column of landmarks (having the identical x- and y-coordinate) at a constant distance d from the X or Y direction of the landmark thus the heading angle θ=0°, with the results from a run given in Table II;

② Experiment 2: The robot travels in a slanting direction with respect to the X-axis or Y-axis of landmark at a certain heading angle θ. The aim of the run is mainly to test the heading precision given by the algorithm, with the results given in Table III;

③ Experiment 3: The robot revolves around a landmark at uniform speed through constant degrees ω per second and we obtain the variation of ω/25 of the

TABLE.II
Results from experiment 1

Video	1	2	3	4	5
	d=20 θ=0°	d=184 θ=0°	d=249 θ=0°	d=312 θ=0°	d=400 θ=0°
mean distance error(mm)	0.20	0.23	0.22	0.32	0.29
mean heading error (°)	0.13	0.11	0.12	0.12	0.15

TABLE.III
Results from experiment 2

Video	1	2	3	4	5
	θ=5°	θ=15°	θ=25°	θ=35°	θ=45°
mean heading error (°)	0.21	0.28	0.27	0.25	0.28

TABLE.IV
Results from experiment 3

Video	1	2	3	4	5
	ω=5° r=150	ω=15° r=180	ω=25° r=150	ω=40° r=180	ω=50° r=200
mean radius error (mm)	0.52	0.48	0.68	0.45	0.57
mean heading error (°)	0.36	0.44	0.48	0.49	0.52

heading angle θ for each frame, with the revolving radius set to be fixed r. The purpose of this run is to validate the accuracy of algorithm-acquired heading angle and position, with the results shown in Table IV.

As shown in Tables II – IV, from the video emulation we obtain the high-precision robot positioning and heading angle, with their errors being very small and no error accumulation as a function of time and distance thus meeting the need of indoor positioning and monitoring. Furthermore, the errors in positioning and orientating are marginally larger in Experiments 2 and 3 than in Experiment 1. Analysis yields that the largeness is due entirely to the fact that in the simulation video there occurs landmark rotation, and this shortcoming can be removed using a bi-linear interpolation algorithm. Therefore, interpolation errors are unavoidable in the produced emulation video, thereby affecting subsequent processing of images to augment error in calculation.

3）Real-Time Experiment

To illustrate the real-time character of the method used, an experiment is conducted on the pieces of emulation video and actual motion video (25 images/sec. and 720×576), and the operational time is computed by means of the timing API function of the Windows, leading to the results shown in Table V. It is seen that the mean rate is approximately 12 fps on average, for the scheme, which satisfies the fundamental requirement.

TABLE.V
Calculated time using the algorithm.

serial video	1	2	3	4	5
frames	76	112	151	92	186
Total time (sec.)	5.7	8.2	12.4	7.8	14.3
processing time(ms)	75	73	82	84	77

4）Comparison Experiment

From experiment 1) and experiment 2) above and many times measurement, it is shown that the mean error of position is less than 1.5mm, and the mean error of heading angle is less than 1°, which is more accuracy than 3° which is achieved in [2].

V. CONCLUSION

A method for the robot indoor position and orientation on the basis of a 2D barcode principle is presented. In the paper, a kind of landmark which contains the position information and has a certain ability of automatic correcting error is proposed. The description of how to identify the landmark and how to use the algorithm for locating and orientating are described. The experiments show that the method of indoor positioning and orienting is marked by simplicity of operation and landmark making, higher robustness/accuracy and good real-time character. Although it is required to change part of the indoor environment, for example, sticking multiple landmarks on the ceiling in accordance with a fixed rule and also to determine the proportional scale by experiment when the method is used, yet the scheme is characterized by making easily landmark, low cost, operational convenience and higher robustness. For this reason, the method can be used as a scheme of the autonomous positioning and orienting for an indoor robot in conjunction with real-time monitoring. For example, it can be used in warehouse environment, where the landmarks are stuck in the ceiling one by one as row-column order (the number of landmarks is depended on the real environment), and the camera mounted in the forklift truck. Using the proposed method the current position and heading angle of the forklift truck are calculated and send to the server, so that not only the administrator can arrange the task and know where the forklift trucks are in navigational map, the forklift trucks automatic driving and loading/unloading merchandise combined with RFID label can be implemented.

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