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Design, Modeling and Moving Object Detection of Omni-directional Vision System Applied in Autonomous Soccer Robot

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Abstract

The autonomous soccer robot with conventional vision cameras has limited fields of view which can be overcome by moving the robot, thus increasing the control difficulty. Omni-directional vision system uses a combination of lenses and mirrors placed in a carefully arranged configuration to capture a much wider field of view. This paper introduced study on omni-directional vision system applied in autonomous soccer robot and its imaging model. Mirror parameters of omni-directional vision sensor were designed using condition and equation of single viewpoint constraint, and dimension of the omni-directional vision system was determined. A set of models including reflect and refraction model were built. The relation between image point and corresponding world point was determined that can offer essential model and algorithm for omni-directional image process. Then, moving object detected technology based on omni-directional vision system is introduced. By the low resolution characteristic of omni-directional correction image, the algorithm effectively deals with problems of the noise and shadow during the abstraction of the foreground. Their practicability is tested through the simulation and real image experiments.

Keywords - omni-directional vision, autonomous soccer robot, single viewpoint constraint, moving object detection

1. INTRODUCTION

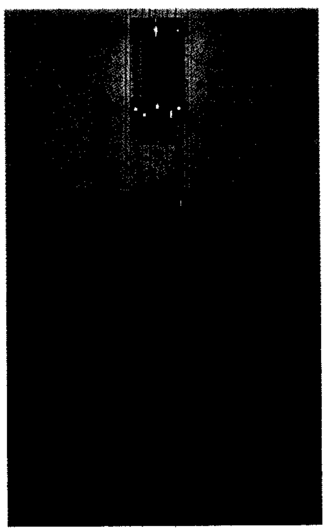

Fig.1 The soccer robot with omni-directional vision system

Autonomous soccer robot is the robot with necessary sensors and controllers which can search, go after and kick ball without man-made information input and control. Because the most of outer environment information comes from vision sensors, they are the most important sensors for robot. Robot can obtain the position information in field and distance with respect to goal, ball and obstacles, which offer necessary data for decision-making system. The field of view of the robot can reach 360° horizontally by using omni-directional vision sensor and it resolves the limited field of view of conventional vision cameras. Fig.1 shows the structure of the soccer robot with omni-directional vision system.

Now days there are many researches in omni-directional vision system. Omni-directional vision system, also called catadioptric vision system, was first raised by Rees in 1970 [1], and Yagi, Hong, Yamazawa did detailed research in their own study. Nayar brought forward an ideal omni-directional imaging system using parabolic mirror after geometrical analysis of all kinds of omni-directional vision systems. The imaging process is introduced in [2] and [3]. The omni-directional vision systems

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made of different mirrors were presented in [4] [5] [6]. Reference [7] described application of omni-directional vision system in vision navigation.

According to international soccer robot game rules, this paper designs the omni-directional vision sensor system and builds its mathematical model. Then, moving object detected technology based on omni-directional vision system is introduced. Finally the simulation and real image experiments results show that the model is practicability and the presented method to recognition and detection a moving object based on omni-directional vision is fast and effective.

2. DESIGN OF OMNI-DIRECTIONAL VISION SYSTEM OF AUTONOMOUS SOCCER ROBOT

2.1. System Structure and Function

The system is composed of omni-directional vision sensor made by mirror and CCD camera, and the computer with image grasper as shown in Fig. 2. The omni-directional vision sensor is fixed on the top of the robot, and the CCD camera is placed in its bottom and mirror in top. The mirror is enveloped in the protecting cylindrical bucket made by colorless plastic, and don't affect the field of view. Optical axis of CCD camera lens and centre axis of mirror is co-line. Reflection surface of mirror towards floor and it reflects image information in 360° horizontal in the field to CCD camera to obtain the omni-directional image.

Omni-directional vision sensor is connected with computer system. During the game, sensor captures the scene information and delivers it to computer which deals with the digital image to achieve the necessary positioning information.

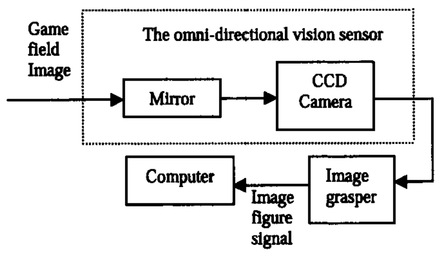


Fig.2 Graphical presentation of omni-directional vision system

2.2. Design of Omni-directional Vision Sensor

2.2.1. Mirror Choice

In omni-directional vision systems, lens of CCD camera refracts and mirror reflects rays. The omni-directional vision system can be divided into single viewpoint and non-single viewpoint imaging system, by whether they have a unique effective viewpoint. Modeling process of single-viewpoint is simple and it can get the image easier to cope with, so our design chooses this kind single viewpoint imaging system. Hyperbolic mirror, parabolic mirror and ellipsoidal mirror can be used to construct the single viewpoint imaging system. Inner surface of ellipsoidal mirror is its work surface which limits its field of view. Parabolic mirror must work with telecentric lens, which is very expensive, so its use is limited greatly. Hyperbolic mirror is the optimal choice in our design duo to its low cost, large field of view and good imaging effect.

2.2.2. Condition and Equation of the Single Viewpoint Constraint

Single viewpoint imaging system satisfies single viewpoint constraint. The single viewpoint constraint requires that each incoming ray passing through the pinhole of the camera (that was reflected by the mirror) would have intersected an effective viewpoint if it had not been reflected by the mirror [8]. We now derive geometry relationship of single viewpoint omni-directional vision system is that the direction of incoming ray relative to each pixel can be attained after the direction of reflect ray is known. If the position of world point and viewpoint is known, we can determine the direction of incoming ray and then attain the position of image point relative to world point based on the condition that the incoming angle equals to reflect angle. So we can draw the conclusion that imaging system satisfying single viewpoint constraint can construct the projection between each image point and corresponding world point.

The virtue of the single viewpoint lies in simplifying geometry model of imaging system, enhancing field of view and changing omni-directional image into projecting one with a little distortion coming from conventional camera so that tractable image is easily processed using general method after being calibrated.

Without loss of generality we can assume that the CCD camera pinhole p lies at the origin of a Cartesian coordinate system. Suppose that the effective viewpoint is located at the point v. We can assume that the z-axis lies in the direction $\overrightarrow{pv}$. The r-axis is orthogonal to z-axis, and we try to find the 2-dimensional profile of the mirror ($z(r)=z(x,y)$, where $r=\sqrt{x^2+y^2}$). If the distance from v to p is denoted by the parameter 2c, we have $v=(0,2c)$. See Fig. 3 for an illustration of the coordinate frame. We denote the angle between an incoming ray from a world point and the r-axis by θ. Suppose that the reflected ray of this ray passes through the point p, this incoming ray must pass through the point v. Suppose we denote the angle between the reflected ray and the r-axis by α , the angle between the z-axis and the normal of mirror by β . We can know the angle between the incoming ray and the normal of mirror is $\gamma+\beta$ base on the theory that the angle of incidence must equal the angle of reflection. We assume the ray intersects the mirror at the point (r,z), we have the relationship:

$$\tan\theta=(2c-z)/r. \tag{1}$$

$$\tan\alpha=z/r. \tag{2}$$

$$dz/dr=-\tan\beta. \tag{3}$$

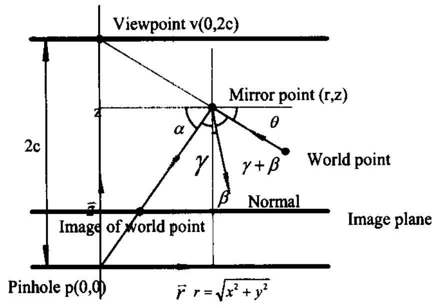


Fig.3 The solution diagram of single viewpoint constrain equation

Using trigonometric function, we have:

$$2\tan\beta/(1-\tan^2\beta)=(\tan\alpha-\tan\theta)/(1+\tan\alpha\tan\theta). \tag{4}$$

Substituting (1), (2), (3) to (4) yields a quadratic first-order ordinary differential equation:

$$r(2c-2z)(dz/dr)^2-2(r^2+2cz-z^2)dz/dr+r(2z-2c)=0. \tag{5}$$

Resolving this equation, we have:

$$(z-c)^2-r^2(k/2-1)=c^2(k-2)/k. \quad (k\geq 2). \tag{6}$$

$$(z-c)^2+r^2(1+2c^2/k)=(k+2c^2)/2. \ (k>0). \tag{7}$$

Equation (6) and (7) define the complete class of mirror surface curves which satisfy single viewpoint constraint and different values of c and k determine different theoretic solutions. The physical meaning of c is the half distance between camera pinhole and viewpoint, so it must satisfy c>0, but its value can not be too large considering the compactness of system. After the constant parameter c is determined, different k designed by vertical field of view of system decides the shapes and curvatures of mirror. The solutions that don't satisfied the condition of c>0 and k>0 are degenerated and cannot be used to construct real sensors with a single effective viewpoint. Ellipsoidal, parabolic and hyperbolic mirror satisfy the condition of single viewpoint. Conic mirror and spherical mirror are degenerate solutions which can be used to construct vision sensors with large field of view, but they are not the single viewpoint imaging system.

2.2.3. Determination of System Dimension of Omni-directional vision Imaging System

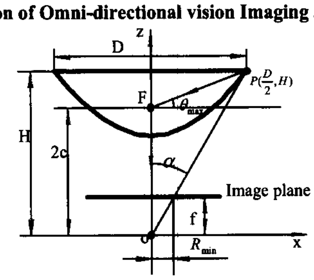


Fig.4 The diagram of mirror design

System dimensions include H, the distance between mirror and camera pinhole, and mirror caliber D [9]. It is symmetrical about optical shaft, and imaging plane is rectangle. Analyze the cross-section passing through CCD camera pinhole and shorter border of the imaging plane. Let $R_{\min}$ the shortest distance between corner point of sensitive part and image centre, f lens foci. From Fig. 4, we have:

$$\tan\alpha = R_{\min} / f = D/2H \cdot \tag{8}$$

During the design, the CCD camera is chosen according to the requirement, then and $R_{\min}$ and f are determined. H should be decided by the game rule. D can be achieved from (8).

2.2.4. Determination of Surface Parameter of Hyperbolic Mirror

CCD camera pinhole is placed in one of the hyperbolic mirror focus, so reflect ray focusing on another focus must pass through the pinhole according to hyperbolic optics property, and imaging in the image plane. Because hyperbolic is revolving symmetry, analysis in xoz plane is enough.

If k>2and c>0, equation (6) denotes hyperboloid:

$$(z-c)^2/\left(c\sqrt{(k-2)/k}\right)^2 - x^2/\left(c\sqrt{2/k}\right)^2 - y^2/\left(c\sqrt{2/k}\right)^2 = 1 \cdot \tag{9}$$

Projecting (9) to xoz plane and getting the following hyperbolic:

$$(z-c)^2/\left(c\sqrt{(k-2)/k}\right)^2 - x^2/\left(c\sqrt{2/k}\right)^2 = 1 \cdot \tag{10}$$

Coordinate of P in the bottom of mirror is (D/2, H), P is a point in hyperbolic so its coordinate should satisfy hyperbolic equation:

$$(H-c)^2/c^2(k-2)/k - D^2 \cdot k/8c^2 = 1 \cdot \tag{11}$$

Angle between the ray passing through P and focus F and X axis is max elevation $\theta_{\max}$ of the system in vertical direction. From Fig. 4, we have:

$$\tan\theta_{\max} = 2(H-2c)/D \cdot \tag{12}$$

$\theta_{\max}$ is determined by the design, solving (11)and (12), getting c and k, substituting c and k to (9), achieving the mirror equation of the hyperboloid mirror.

3. MODELING OF OMNI-DIRECTIONAL VISION IMAGING SYSTEM

3.1.. Getting Image Point from World Point

Placing the coordinate origin in the pinhole of CCD camera, both optic axis and mirror shaft coincide with z axis. Coordinates of every point are shown in Fig. 5.

Intersection Point of incoming ray and mirror X_m satisfies the incoming ray equation, so we have:

$$x_m / x_0 = y_m / y_o = (z_m - 2c)/(z_o - 2c) \cdot \tag{13}$$

Moreover, X_m also satisfies mirror equation, so

$$P^T \cdot Q \cdot P = 0 \cdot \tag{14}$$

where ,

$$\boldsymbol{Q} = \begin{bmatrix} 2-k & 0 & 0 & 0 \\ 0 & 2-k & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 2(2-k)c^2/k \end{bmatrix}, \boldsymbol{P} = \begin{bmatrix} x_m \\ y_m \\ z_m - c \\ 1 \end{bmatrix}$$

Relation between X_m and image point X_i can be expressed by the following matrix:

$$\begin{bmatrix} x_i \\ y_i \\ z_i \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1/f & 0 \end{bmatrix} \cdot \begin{bmatrix} x_m \\ y_m \\ z_m \\ 1 \end{bmatrix}. \tag{15}$$

So the corresponding relation of world point and image point is built.

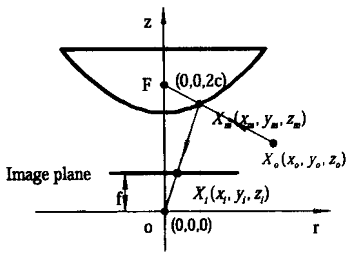


Fig.5 The diagram of vision system modeling

3.2. Getting World Point from Image Point

Conic can be described by the following parameter equation:

$$z(t)=t,\ r(t)=\sqrt{(e^2-1)t^2+2pt-p^2}\ . \tag{16}$$

Where e denotes eccentricity, p is the foci of conic. This equation indicates hyperbola when e>1, point coordinates on hyperboloid mirror satisfy $S_r(t)=[z(t),r(t)]$.

Direction vector of reflection ray can be depicted as following from Fig. 6:

$$V_r(t)=\left[t,\sqrt{(e^2-1)t^2+2pt-p^2}\right]. \tag{17}$$

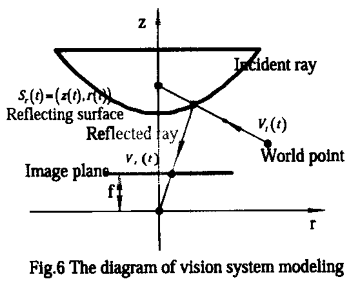


Fig.6 The diagram of vision system modeling

Let mirror normal vector $N_r(t)$, from reflection principle, the direction vector of incoming ray can be achieved [10]:

$$V_i(t)=V_r(t)-2N_r(t)(N_r(t)\cdot V_r(t)). \tag{18}$$

When coordinate of image point is known, direction vector of reflecting ray can be determined. Direction vector of corresponding incoming ray can be gotten from (18). Finally we obtain the coordinate of world point.

4. MOVING OBJECT DETECTION OF OMNI-DIRECTIONAL VISION IMAGING SYSTEM

4.1. Omni-directional Image Unwrapping

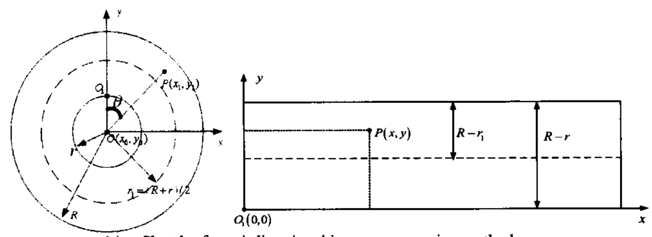
The omni-directional image can be unwrapped by space transformation. Space transformation includes direct and indirect method [11]. Both the methods establish the coordinates mapping relationship between the omni-directional image and unwrapped image. Direct space transformation is that we solve the unwrapped imaging point coordinate from the omni-directional image one by the formula 19, and then put the pixels value of the omni-directional image point (x_1, y_1) to the unwrapping image point (x, y). The formula as following, where F_x and F_y are the direct space transformation function:

$$\begin{cases} x = F_x(x_1, y_1) \\ y = F_y(x_1, y_1) \end{cases}. \tag{19}$$

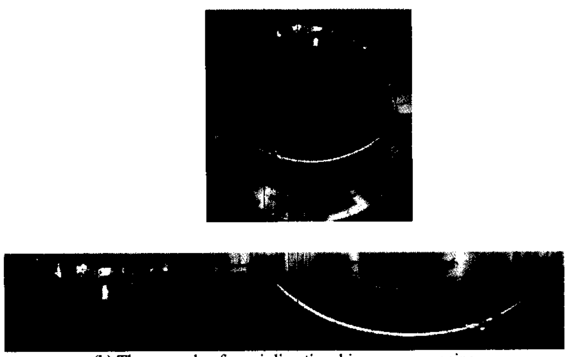
$$\begin{cases} x_1 = G_x(x, y) \\ y_1 = G_y(x, y) \end{cases}. \tag{20}$$

Indirect space transformation is that we solve the omni-directional image point coordinate by the formula 20, and then put the pixels value of the omni-directional image point (x_1, y_1) to the unwrapping image point (x, y).

Where G_x and G_y are the direct space transformation function. Two problems are produced by using the direct space transformation [12]. One is that the null image points emerge when we stretch and enlarge the image. Another one is that several original image points corresponding to one on the compression area. Both of the problems can mess up the pixels relation of the original image, which bring up the bad unwrapping image. Take consider of it, we adopt the indirect space transformation to confirm the relation of omni-directional image and unwrapping image. This method also can be called converting transformation. We start from the output pixels, mapped them one by one to the input image. It helps us to confirm the pixels value. However, after converting, the integer coordination value of the output pixel becomes floating one. So the pixels value should be solved by the interpolation. There are some interpolation methods such as the nearest neighbour algorithm, bilinear interpolation, high order interpolation method etc. The nearest neighbour algorithm is easy but without high accuracy, high order interpolation method has high accuracy but takes a lot of time. We prefer the bilinear interpolation to attain high accuracy and meet the need of real-time.



(a) Sketch of omni-directional image unwrapping method


(b) The example of omni-directional image unwrapping
Fig.7 Unwrapping omni-directional image

For the sake of accelerating the operation speed of unwrapping, fast approximation algorithms would be used [13]. In Figure 7a, r is the inner radius, R is the outer radius. The region between the outer radius and inner radius is the effective area of the image. Here is the rule of unwrapping:

1. Keep the y axis.

2. The intersection O_1 of y axis and inner radius in Figure 7a, corresponding to the point O_1 in Figure 7b.
3. The width of unwrapped image equals to the perimeter of the dashed circle in omni-directional image.
The dashed circle is the concentric circles of the outer and inner circle, where $r_1 = (r+R)/2$.

Suppose the coordinate of circle centre O in omni-directional image is (x_0, y_0). Origin coordinate in unwrapping image is $O_1(0,0)$. Any point $P=(x,y)$ in unwrapping image is corresponding to (x_1, y_1) in omni-directional image. Formula 21 gives the relation between (x,y) and (x_1, y_1):

$$\begin{cases} \theta = x/r_1 \\ r_1 = (r+R)/2 \\ x_1 = x_0 + (r+y)\sin\theta \\ y_1 = y_0 + (r+y)\cos\theta \end{cases} . \tag{21}$$

This method is a process of image Interpolation substantively. After unwrapped, the image upper the dashed line is landscape orientation compressed, that below the dashed line is landscape orientation stretched, while the points on the dashed line is constant. Figure 7b is the example of omni-directional image.

4.2. The Distortion Correction of Unwrapped Image

The unwrapped omni-directional image has large distort because of compression and stretch process, which is disadvantage to image identification, analysis and judgment. It's necessary to correct the distorted image for fix quantify image analyze such as moving object detection. Using geometrical transform to correct the position of each pixel in the distorted image, we can reconstruct the pixel original space relations. Here we just expect to correct the distortion generated by mirror, i.e. revert the unwrapped image to the effect which obtained by common CCD lens. Hence, aim image for distortion correction can be obtained by common lens and distorted image through omni-directional vision system, then, we can ascertain the relationship between the aim image and the distortion image.

The image distortion is nonlinear, it can be expressed by polynomial transform between coordinate.

Let $g(u,v)$ the aim image, it turns into $f(x,y)$ because of the influence of the geometry deformation. Here (u,v) is the coordinate of aim image, (x,y) is the coordinate of distorted image. The relation between them is:

$$\begin{cases} x = \sum_{i=0}^{n}\sum_{j=0}^{n-i} a_{ij} u^i v^j \\ y = \sum_{i=0}^{n}\sum_{j=0}^{n-i} b_{ij} u^i v^j \end{cases} . \tag{22}$$

In formula 22, n is the rank of the polynomial, and a_{ij} 、 b_{ij} are unknown coefficient which can be computed by least square method.

Suppose object function is:

$$I = \sum_{k=1}^{L}\left(x_k - \sum_{i=0}^{n}\sum_{j=0}^{n-i} a_{ij} u_k{}^i v_k{}^j \right)^2 . \tag{23}$$

If we expect to make it minimum, set:

$$\frac{\partial I}{\partial a_{st}} = 2\sum_{k=1}^{L}\left(\sum_{i=0}^{n}\sum_{j=0}^{n-i} a_{ij} u_k{}^i v_k{}^j - x_k \right) u_k{}^s v_k{}^t = 0 . \tag{24}$$

So:

$$\sum_{k=1}^{L}\left(\sum_{i=0}^{n}\sum_{j=0}^{n-i} a_{ij} u_k{}^i v_k{}^j \right) u_k{}^s v_k{}^t = \sum_{k=1}^{L} x_k u_k{}^s v_k{}^t . \qquad ((25)$$

Similarly, we have:

$$\sum_{k=1}^{L}\left(\sum_{i=0}^{n}\sum_{j=0}^{n-i} b_{ij} u_k{}^i v_k{}^j\right) u_k{}^s v_k{}^t = \sum_{k=1}^{L} y_k u_k{}^s v_k{}^t \ . \tag{26}$$

L is the number of controlling point pairs, s=0,1…,n, $s+t \le n$. Formula 25 and formula 26 are two linear equations with M equations, each equation contains $M=(n+1)(n+2)/2$ unknown value. We can compute a_{ij}、b_{ij} through above two formulas, then take them into formula 22 to implement the transform between the two coordinates. The bigger the n, the more accurate the coefficient of distortion and the more compute time will be taken. In this paper we set n=3, that is, M=10, so the Formula 25 and formula 26 can be written as fallowing:

$$\begin{aligned} x = a_{00} + a_{01}v + a_{02}v^2 + a_{03}v^3 + a_{10}u + a_{11}uv \\ + a_{12}uv^2 + a_{20}u^2 + a_{21}u^2v + a_{30}u^3 \end{aligned} . \tag{27}$$

$$\begin{aligned} y = b_{00} + b_{01}v + b_{02}v^2 + b_{03}v^3 + b_{10}u + b_{11}uv \\ + b_{12}uv^2 + b_{20}u^2 + b_{21}u^2v + b_{30}u^3 \end{aligned} . \tag{28}$$

The two equations are made of 10 equations respectively, each of which has 10 unknown values, so we need 10 controlling points to ascertain the distortion coefficient. This correct method is simple, efficiency and accurate.

4.3. Adaptive Background Modeling Algorithm

Figure 8 is the background modeling algorithm flowchart. To extract T frame image in W sampling speed. $V_t(i,j)$ is the pixel value of the t frame image at point (i,j). $Y(i,j)$ is the pixel value of the background modeling B at point (i,j). All points (i,j) comply the formula 29 to execute median filter, the $Y(i,j)$ value of the background modeling can be solved from the value of $V_t(i,j)$.

$$Y(i,j) = \left\{ V_q(i,j) \middle| \min_{V_q(i,j)} \sum_{P=1}^{T} \left| V_p(i,j) - V_q(i,j) \right| \right\} \cdot \tag{29}$$

Then the updating of the original background is achieved. The current background image is obtained.

The value of the sampling speed W is adjusted based on speed of the moving target. If W is too small, then the sampling speed will be far below the speed of the moving object. In this case, the moving object may be regarded as the still scene information to be reserved to the background image. However, if it is too large, the real-time can not be satisfied.

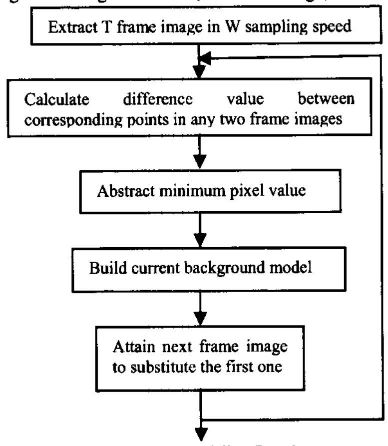


Fig. 8 The background modeling flowchart

4.4. Moving Object Recognition and Detection

4.4.1 Deduction of the Background

The image and background is treated by difference method. After that, the image of the moving object can be attained. The detail stages are showed as follows:

Calculate the pixels value of the foreground image Ω.

$$Z(i,j)=\left|X(i,j)-Y(i,j)\right| \quad (i,j)\in\Omega \cdot \tag{30}$$

Where, $X(i,j)$ is pixels value in the current frame; $Y(i,j)$ is the pixels value of point (i,j) in background frame; $Z(i,j)$ is the pixels value of point (i,j) in foreground frame.

4.4.2. Edge Detection of the Foreground Image

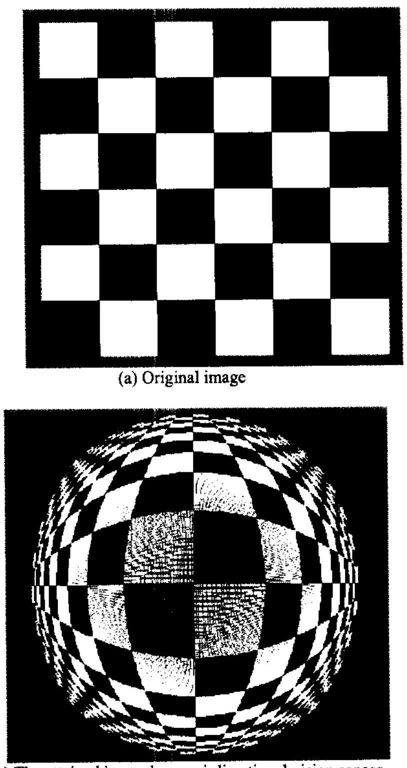
Extracting the foreground image, then the image enhancement is carried out by linear transformation contrast enhancement. Noise can be removed by median filter method after binary. Median filter method operates easily, and can protect the edge well. Finally do the edge detection by canny operator which has great edge testing performance. Noise and shadow has been separated from the moving target in the low resolution corrected image. At last we get the image only with the edge information of the object. The effective of the edge detection is perfect.

5. SIMULATION AND REAL IMAGE EXPERIMENTS

5.1. The Model Simulation Experiments

The experiment equipment is 1/3 inch CCD camera with $R_{\min}=1.8$mm, f =4mm, image resolution is 752×582. H is 120mm according to the height of robot is 800mm in game rule. From (8) we have D=108mm, and P (54,120). Let the max vertical elevation of omni-directional sensor $\theta_{\max}=15$. From solution (11) and (12), we get c=52.7, k=4.2, and the hyperbolic mirror equation from (9) is $(z-52.7)^2/1455-x^2/1323-y^2/1323=1$.

Area of game field is 12000×8000mm in game rule, we construct a 12000×12000mm origin image as show in Fig. 9(a).



(a) Original image

(b) The attained image by omni-directional vision sensor

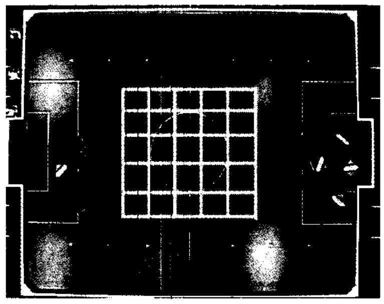
Fig.9 Simulate experiment

Assume that omni-directional vision sensor is placed 500mm above the image center. Simulation attained image through reflect model and camera pinhole model is shown in Fig. 9(b).

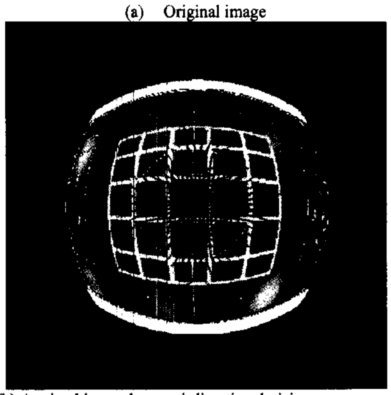
5.2. The Model Real Image Experiment

We place a check board in center of real game field as show in Fig. 10(a). Omni-directional vision sensor is placed 500mm above field. Image of field attained through reflect model and camera pinhole model is shown in Fig. 10(b).

Through simulation and real image experiments, we find that the attained image is a distortion omni-directional image which can be calibrated. The effect of image is basically ideal. The omni-directional vision system designed in this paper satisfies autonomous soccer robot game rule and can obtain omni-directional image which can be easily processed, so the system is very useful in practice.



(a) Original image

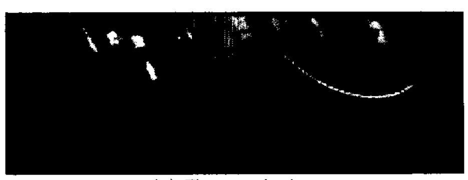


(b) Attained image by omni-directional vision sensor

Fig.10 Real image experiment

5.3. Moving Object Detection Experiment

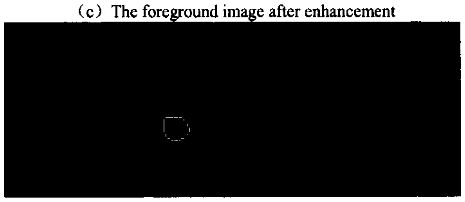
We do many experiments by the image obtained through omni-directional vision system lie on autonomous soccer robot to prove algorithm in this paper. Fig.11a, b, c, d is corresponding to correction image, background image by adaptive background modeling algorithm, the foreground image after enhancement, the detection image respectively. The result of detection is perfect. Result of detection for unwrapped image is not been corrected is shown in Fig.11e. Fig.11f is detection result by ordinary background modeling algorithm. The effect of noise and shadow is still obvious.



(a) The correction image

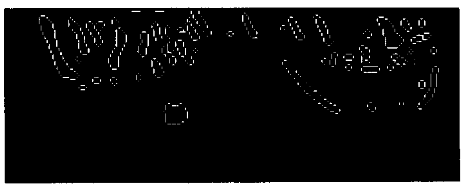
(b) Background image

(c) The foreground image after enhancement



(d) The detection image

(e) The detection image of unwrapping image



(f) The detection image by ordinary background modeling algorithm

Fig.11 The experiment results of moving objection detection

6. CONCLUSION

The omni-directional image has been widely used in the areas such as robot navigation, detection, video surveillance and object tracking, so study on omni-directional vision system and omni-directional image is very necessary. Main works of this paper consist of designing mirror of omni-directional vision sensor and system dimension, building a total set of mathematical model including reflection model of mirror and camera pinhole imaging model, determining the relation between image point and world point and offering essential model and algorithm for omni-directional image process. Simulation and real image experiments verify the system's practicability. The design thought and model advanced in this paper can be used as reference in developing the similar system and researching the omni-directional vision imaging system.

A moving object recognition and detection algorithm based on omni-directional image characteristic is proposed for moving object with static camera. Omni-directional image is unwrapped through a fast unwrapping algorithm. Correction of unwrapped image is performed based on nonlinear distortion model. An adaptive background modeling method is used, which is real-time updated. Final, the foreground is obtained to detect moving object. By the lower resolution of omni-directional correction image, the algorithm effectively deals with problems of the noise and shadow during the abstraction of the foreground. Experiment results show that the presented method is fast and effective.

REFERENCES

1. Ishiguro H. (1998). Development of low-cost compact ODVS and their applications. Proc. Int. Conf. Information Systems, Analysis and Synthesis, 433-439.
2. Nayar S K. (1997). Catadioptric omnidirectional camera. Proc. Of IEEE Conf. on Computer Vision and Pattern Recognition, 482-488.
3. S. Baker, S. Nayar (1998). A theory of catadioptric image formation. In Proc. International Conference on Computer Vision, 35-42.
4. Derrien S, Konolige K (2000). Approximating a single viewpoint in panoramic imaging devices. Proc. Of Int. Conf. on Robotics and Automation, 3931-3938.
5. Zeng Jiyong, Su Xianyu (2003). Paraboloidal catadioptric omnidirectional imaging systems. J. Journal of Optoelectronics · Laser, vol. 14, no. 5, 485-488.
6. Zeng Jiyong, Su Xianyu (2003). Catadioptric omnidirectional system with undistorted imaging for horizontal scene. J. Acta Optica Sinica, vol. 23, no.5, pp. 636-640.
7. Y. Yagi, S. Kawato, S. Tsuji (1994). Real-time omni-directional image sensor for vision-guided navigation. J. IEEE Trans. On Robotics and Automation, vol.10, no. 2, 11-22.
8. Baker S, Nayar S K (1999). A theory of single-viewpoint catadioptric image formation. J. International J. Computer Vision, vol. 35, no. 2, 175-196.
9. Zeng Jiyong, Su Xianyu (2003). Hyperboloidal catadioptric omnidirectional imaging system. J. Acta Optica Sinica, vol. 23, no. 9, 1138-1142.
10. S. Rahul, Michael D. Grossberg, Shree K. Nayar (2001). Non-single viewpoint catadioptric cameras: Geometry and Analysis. USA: Columbia University.
11. ZHANG Jian, DUAN Tao and LIU Ai-dong (2003). Algorithm Research on Correction of Geometric Distortion and its Implement of Software. Optics&Optoelectronic Technology, vol.1,no.2, 60-64.
12. LIU Jingen (2004). A Rectification Algorithm for Photoelectric Image with Distortion Based on Method of Onsite Ascertained Standard. Acta Photonica Sinica, vol.33, no.6, 732-735.
13. PI Wenkai, LIU Hong and ZHA Hongbin (2004). Motion Detection for Human Bodies Basing Adaptive Background Subtraction by Using an Omnidirectional Camera. Acta Scientiarum Naturalium Universitatis Pekinensis, Vol.40, no.3, 458-464.