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An evolutionary method to vision-based self-localization for soccer robots

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Abstract. In this paper, a method using an evolutionary algorithm to automatically set-up the color-feature model of an omnidirectional vision system will be introduced. The mentioned method, in addition to avoiding the issue of over-reliance on lighting conditions when the soccer robot is performing image processing, can also very effectively speed up the parameter setup procedure of the robot vision system. Hence, when the robot is moving in the soccer field, it can finish target object detection and self-localization in real time. In order to verify the effectiveness of the mentioned method, tests have been conducted under different bad lighting conditions, and the experimental results show that the soccer robot can always set up the parameters of the vision system. It can also set up the color-feature model that is applicable to the operational environment at that moment and detect target objects such as goals and the field. Meanwhile, through relative location between detected target objects and the robot, self-localization and path planning can be finished.

1. Introduction

The design of intelligent robots has become one of the developmental focuses of international academic research and industry application in recent years, and some advanced industrialized countries have even treated robot competitions as a strategic means to promote domestic creativity teaching. Currently, there are two robot-soccer associations, RoboCup and FIRA, devoting to the promotion of robot soccer games [1,2], and each year, international cup robot soccer games and international forums are held regularly for the exchange of research results. The robot soccer game is interdisciplinary integrated research work covering artificial intelligence, automatic control, image processing, mechanism design, sensor systems and electronic communication. The holding of robot soccer games can internationally promote and stimulate the exchange and development of technology related to artificial intelligence, the strength design of mechanisms and multi-sensor system applications. In order to allow robots the means to play soccer in the soccer field independently, from a practical design aspect, the robot must be able to, from image analysis results, decide the movement direction of the robot body. Meanwhile, it must be able to implement functions such as path planning, avoiding obstacles and dynamic object tracking. Moreover, cooperative strategies among several soccer robots, such as assisting, defending and ball passing, should also be considered. The design process can not only effectively enhance the students' implementation capability, but can also help the incubation of creativity and a collaborative spirit. Hence, its importance has received more and more attention from both academia and industry.

The design of a vision system is core technology for a robot. Although academia has spent several decades studying human vision systems, the related functions and principles of the human eye still cannot be fully understood. Hence, the use of machine vision

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to simulate human vision is a pretty tough challenge. After a robot has used a vision system to complete the image analysis of the peripheral environment, based on recognition and judgment, the robot can then make a correct response. For video input amounts of 30 images per second, if massive features need to be found and compared for each image, it is not difficult to imagine that there is a huge amount of image and operational data hidden behind the vision system of the robot. Not only this, during the processing process, if situations such as optical source conditions or vision angles change, or if the sudden disappearance or emergence of objects in the environment are encountered, a flexible response is needed. That is, when the visional system of a robot is facing environmental changes, its image processing must be very robust. Only when the robot can process environmental uncertainty correctly can its utility goal be reached.

In the field of the robot soccer game of the FIRA association, the appearance of target objects is distinguished by specific colors. Here, the robot is black, the soccer field is a green background painted with white lines, the soccer ball is orange, and the gates at both sides of the field are, respectively, yellow and blue. Therefore, if the robot is to have the capability of identifying the target object in the soccer field, the simplest method is to use the color information of the target object as a feature. After the image is acquired by the omnidirectional camera at the top of the robot, the image information will be transmitted through the YUV color system, and then converted into the RGB color system to be used by the subsequent image analysis module. Digital images, using the RGB color system, could be easily and significantly affected by optical beam changes. Hence, before performing image analysis, we will first use the look-up table method to perform color space transformation from RGB to HSV, so as to reduce the influence of brightness on the color of the object [3]. After completing image transformation, we need to set up the upper and lower limit values of the color of each target object, and set up the color-feature model. Using the setup color feature model, we can then detect and extract target objects, such as balls and gates, from different input images. The process is shown in Figure 1.

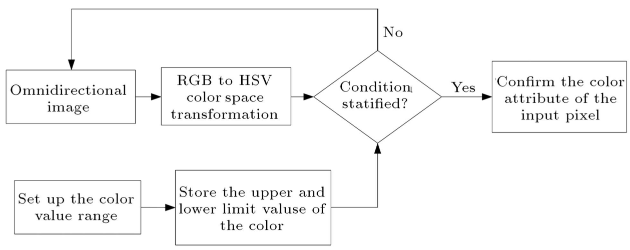


Figure 1. The setup process of the color-feature model of the FIRA robot system.

In the current architecture of FIRA medium-sized soccer robots, the participant must, based on the lighting condition of the operation site, manually set up, one by one, the color range value of each robot on all the target objects in the soccer field, in order to set up a color-feature model that can meet the needs. Such a model construction method, based on the trial and error method, is very tedious and time-consuming. In fact, in the current rules, even in the indoor game, the luminance of the game site still allows a difference within 300 lumens. Hence, the light source within the environment of the game site is not uniform and consistent. As the robot moves in the soccer field constantly, the gray levels and hues of the omnidirectional image acquired will change accordingly, too. Hence, over-simplified video processing architecture cannot satisfy the current situation. It is estimated that several years in the future, the game of a medium-sized soccer robot group will be all in natural light instead of a stable indoor lighting source, and this will bring more stringent challenges to the vision system design of the robot.

The evolutionary computing technique is an optimal solution search mechanism that is constructed based on a biological evolutionary concept. All kinds of difficult combinatorial optimization problems can be solved by its use. After almost 30 years of effort, evolutionary computing has its own unique research field, which includes Evolution Strategy (ES), Evolutionary Programming (EP), Genetic Algorithm (GA), Simulated Annealing (SA), PSO [4], and Ant Colony Optimization (ACO). All these computing techniques have respective advantages and disadvantages: Take GA, for example, it has advantages such as a parallel multi-point search and easy integration with other methods. However, the convergence speed at solving problems is not so good. Although SA has better convergence characteristics, parallel implementation is difficult [5]. Some scholars try to use the swarm intelligent behavior of natural phenomena to develop a hybrid optimization algorithm [6,7], so that complementary effects, among different methods, can be achieved. PSO, among lots of algorithms, has characteristics such as less parameter settings, robustness and high convergence speed [8]. Currently, in academia, much research has applied PSO in image processing, with larger amounts of computing data, in pattern recognition or video processing [9-12], and all results prove that it has a good performance on complicated problems.

In the present paper, we have presented a design method for a robot evolutionary vision system based on PSO, which allows the robot to, before the operation, follow the light source environment, and make automatic evolutions for the needed color-feature model. Hence, it can replace the traditional time-consuming method based on trial and error for all

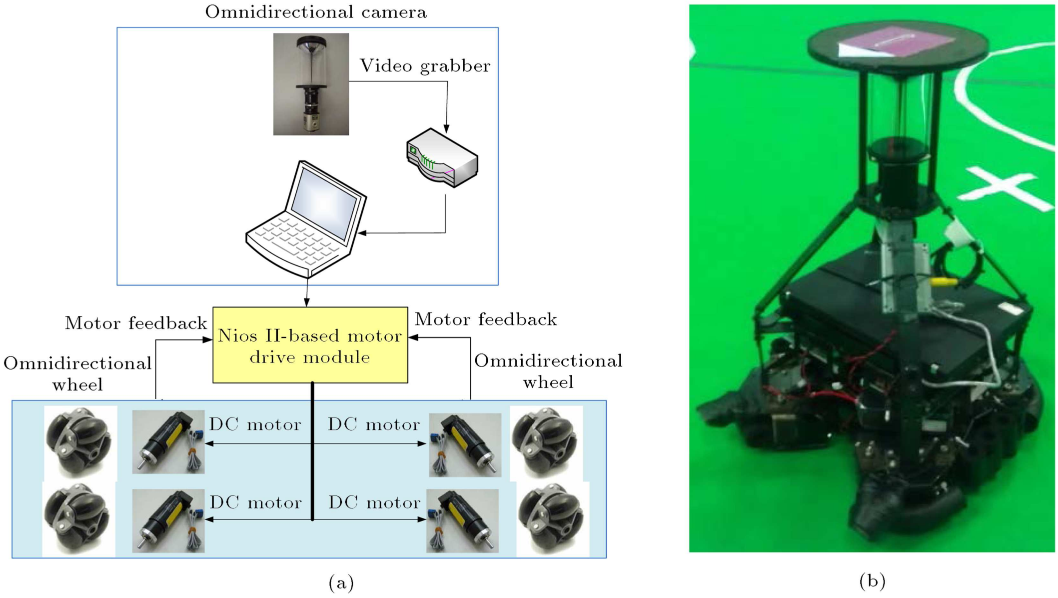


Figure 2. FIRA medium-sized soccer robot: (a) Hardware architecture; and (b) actual appearance.

kinds of parameter setup. Eventually, the robot can be more robust to cope with future ever complicated and changing game environments.

2. Introduction of FIRA medium-sized soccer robot system

The architecture of FIRA medium-sized soccer robots can be divided into a top layer omnidirectional vision system, a motor drive module and a bottom layer omnidirectional moving mechanism. Figure 2(a) and (b) show its appearance.

2.1. Omnidirectional vision system

A Medium-sized soccer robot uses an omnidirectional camera to construct a vision system to acquire images in the peripheral environment. The output NTSC analog signal, after A/D conversion into a digital signal and after image processing and analysis, will be able to display the information of the environment. Robots equipped with omnidirectional cameras, during the game process, do not need to rotate the camera specifically to know the peripheral images of 360 degrees, which effectively enhances its detection capability and change-coping speed within the environment. The horizontal vision of an omnidirectional camera is 360 degrees, and the vertical vision is -10 degrees to 55 degrees, which are shown in Figure 3(a). Since an omnidirectional mirror has its image formed through optical reflection of the peripheral image, which leads to serious distortion on the actually observed image, its image formation is of concentric divergence, and an object that has longer distance from the robot body itself will receive more serious distortion, as shown in Figure 3(b).

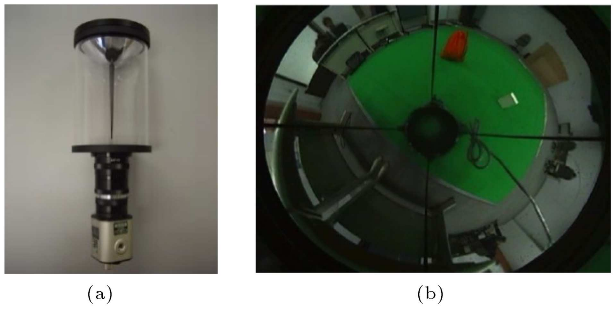


Figure 3. Omnidirectional visional system: (a) Appearance of omnidirectional visional camera; and (b) omnidirectional image.

2.2. Motor drive module and omnidirectional moving mechanism

This study has used an Altera Nios II Development board to construct a motor drive module to control the rotation of the motor. The four-wheeled omnidirectional chassis structure allows the robot to make 360 degrees omnidirectional movements on the ground. Thus, the mobility of the robot is effectively enhanced. Figure 4 shows the relationship between the four-wheeled chassis design structure and velocity vectors, and the four-wheeled movement equation is represented in Eq. (1) [13-15]:

$$\begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{bmatrix} = \begin{bmatrix} R\dot{\theta}_1 \\ R\dot{\theta}_2 \\ R\dot{\theta}_3 \\ R\dot{\theta}_4 \end{bmatrix} = \begin{bmatrix} -\sin(\delta) & \cos(\delta) & L \\ -\sin(\delta) & -\cos(\delta) & L \\ \sin(\delta) & -\cos(\delta) & L \\ \sin(\delta) & \cos(\delta) & L \end{bmatrix} \begin{bmatrix} \dot{x}_m \\ \dot{y}_m \\ \dot{\phi} \end{bmatrix}, \quad (1)$$

where v_i is the moving velocity of the ith wheel; $\dot{x}_m$ is the moving speed of the robot on the x_m axis; $\dot{y}_m$ is the moving speed of the robot on the y_m axis; $\dot{\varphi}$

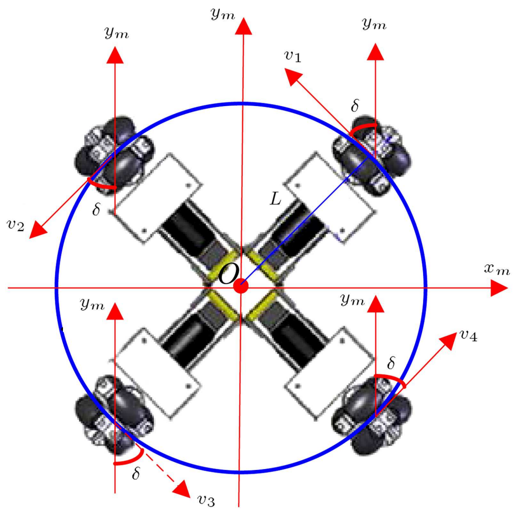


Figure 4. The correlation between the four-wheeled omnidirectional chassis structure and velocity vectors.

is the rotational angular velocity of the robot; L is the distance from the omnidirectional wheel to the omnidirectional movement robot chassis center O; R is the radii of the omnidirectional wheel; and $\dot{\theta}_i$ is the rotational angular speed of the ith wheel.

3. Using PSO to construct the vision system

3.1. Particle swarm optimization

Since Kenney and Eberhart developed the PSO in 1995, it is regarded as an evolutionary computation technique to solve many optimal problems. Based on imitation of simplified social models, PSO can be considered a swarm-based learning scheme, like fish schooling and bird flocking. According to the natural foraging behavior of bird flocking, birds find food by flocking (not by each individual). In the PSO learning process, each single solution is a bird, referred to as a particle. This PSO learning algorithm simulates the swarm-like behavior of natural creatures. The individual particles fly gradually towards the positions of their own and their neighbors' best previous experiences in a huge search space. From this study, it shows that the PSO is given more opportunity to "fly" into desired areas to get better solutions. Therefore, PSO can discover reasonable solutions much faster than other evolutionary algorithms. Like GA, the PSO needs to define a proper fitness function that evaluates the quality of every particle's position. The position, called the global best ($g$best), is the one which has the highest fitness value among the entire swarm. The location, called the personal best ($p$best), is the one which has each particle's best experience. Based on every particle's momentum, and the influence of both personal best ($p$best) and global best ($g$best) solutions, every particle adjusts its velocity vector at each iteration. The PSO learning formula is described as follows [4,9]:

$$\begin{aligned} V_{i,m}(t+1) = {} & \tau . V_{i,m}(t) + c_1 * \mathrm{rand}(\ ) \\ & * (p\mathrm{best}_{i,m}(t) - X_{i,m}(t)) + c_2 * \mathrm{rand}(\ ) \\ & * (g\mathrm{best}_m(t) - X_{i,m}(t)), \end{aligned} \tag{2}$$

$$X_{i,m}(t+1) = X_{i,m}(t) + V_{i,m}(t+1), \tag{3}$$

where m is the dimensional number; i denotes the ith particle in the population; V is the velocity vector; X is the position vector; τ is the inertia factor; and c_1 and c_2 are the cognitive and social learning rates, respectively. Note that these two rates control the relative influence of the memory of particles and the neighborhood.

3.2. Using PSO to automatically set up a color-feature model

As shown in Figure 1, soccer robot uses the color information of the target object to recognize the object. Hence, before each driving of the robot, we have to follow the lighting conditions at that time within the HSV color space and aim at each target object to set up a suitable color-feature model. The HSV color system is formed by information, such as Hue, Saturation and Value, and its advantage is in separating the brightness component from the color information. Hence, the influences of lighting change can be reduced. When these three basic attributes are used to describe the color, it can better fit human sensory recognition, compared to the RGB color system. After completing construction of the color feature model, the soccer robot can use it to analyze the image, and the specific target object meeting the threshold condition can then be recognized.

In this paper, we have used PSO to realize an evolutionary vision system, so that the robot can follow the lighting condition of the environment it is in to make automatic evolutions of the color-feature model it needs. The architecture is shown in Figure 5. Before the start of a game, when both the ball and the robot are settled at fixed positions, at this moment, the soccer robot can, through the PSO algorithm, set up the needed color-feature model to complete the parameter setup procedure before the game.

3.2.1. Encoding of the particle

To achieve the goal of using the PSO algorithm to make the automatic evolution of a color-feature model, we first have to generate an initial population, and the encoding value of each particle in the population represents the solution parameters of a different color-feature model. Evaluation of the capability to successfully extract the target objects is its adaptability to the environment. The encoding form of the particle is shown in Figure 6. According to practical operational

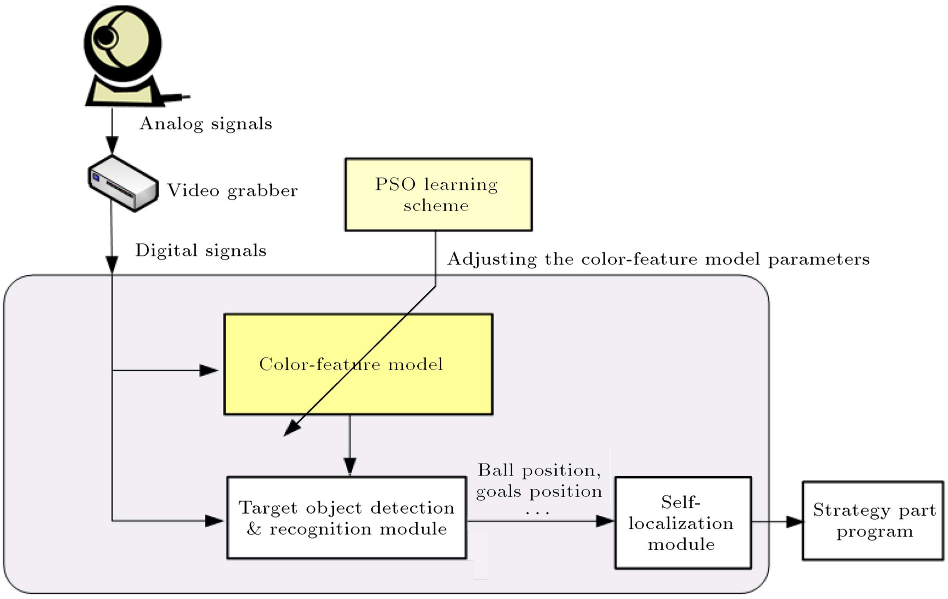


Figure 5. An evolutionary visional system architecture diagram based on the PSO algorithm.

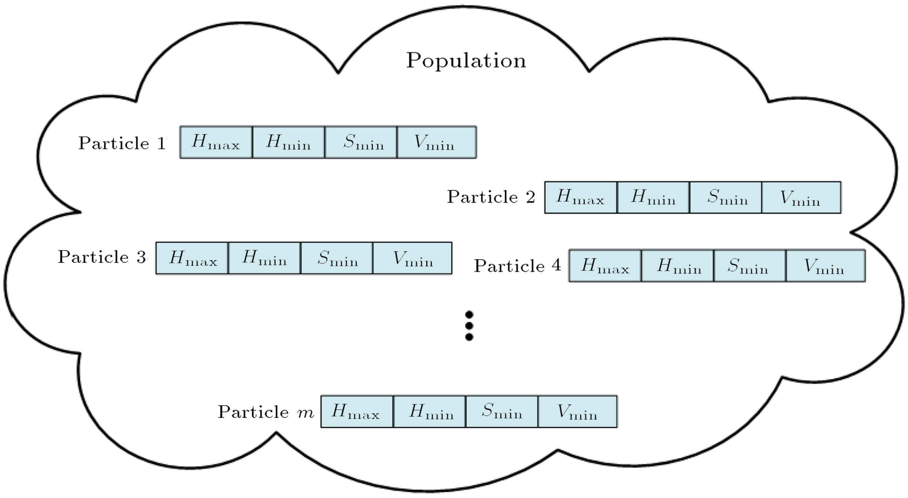


Figure 6. The encoding form of particle.

experience, we have found that under most conditions, when the upper limit values of parameters, such as the saturation and value of the color-feature model, are fixed at maximal values (i.e. $S_{\max} = 100$, $V_{\max} = 100$), it facilitate extraction of the target objects. Therefore, in this research, we have set up the encoding values of the particles as the set of the upper and lower limit values of Hue, and the lower threshold values of saturation and value; that is, $X = \{H_{\max}, H_{\min}, S_{\min}, V_{\min}\}$, and $0 \leqq H \leqq 360$, $0 \leqq S_{\min} < 100$, and $0 \leqq V_{\min} < 100$.

3.2.2. Fitness function evaluation

The fitness function, in the PSO algorithm, is an index used to assess the fitness of a particle to its environment. In this paper, we have used the target object image extracted from an optimal color-feature model using experience value as a template. Then, it is compared, one by one, to the target object image extracted by each particle in the PSO population, to calculate the similarity between each other. Hence, the corresponding fitness value can then be obtained. Eqs. (4) and (5) have explained the method, using implementation of the operation of image subtraction to assess the difference of two target object images:

$$d(f_{\text{Template}}, f_{\text{obtained}}) = \sum_{i=1}^{M}\sum_{j=1}^{N} \left| f_{\text{Template}}(i,j) - f_{\text{obtained}}(i,j) \right|, \tag{4}$$

$$\text{Fitness} = \frac{1}{d(f_{\text{Template}}, f_{\text{obtained}}) + \text{eps}}, \tag{5}$$

where "eps" represents an extremely small value, and

f_{Template} is the standard extracted result of the target objects.

The color-feature model of the soccer robot should be set up completely, according to the lighting conditions, before the game. After the ball and the soccer robot are settled, the robot will then start to perform the automatic setup procedure of the color-feature model. In the setup method, each particle in the PSO algorithm represents a different color-feature parameter set. Then, the parameter set, aiming at the acquired image, can obtain the extracted result, f_{obtained}, for the target object. This result will then be compared to the standard extracted result, f_{Template}, which is stored in advance in the robot. Then, an evaluation value of superior or inferior performance can be obtained. After the finishing of the iteration procedure, the optimal solution can be used to obtain the applicable color-feature model under that lighting condition. Figure 7 illustrates the use of the image subtraction method for assessing the fitness value of the particle. In this figure, the encoding value of each particle corresponds to the extraction judgment condition of one set of the target object. After the subtraction is made between the extracted target object image and the sample image, the difference pixels are represented by red. When the red block is larger, it means the error is larger, hence, the particle should have a smaller fitness value. On the contrary, when the red block is smaller, it means the fitness value is larger.

After completing all particle fitness value assessments, the next thing is to follow Eqs. (2) and (3) to correct the position and movement velocity of all the particles in the population. The search direction will, in the iterative process, gradually approach the position of global optimum.

4. Implementation results and discussions

Figure 8(a) is an omnidirectional image obtained under ideal lighting conditions, and Table 1 shows the parameter values of the color-feature model setup using trial and error. Using the extraction rules in

Table 1. The parameter values of the color-feature model under ideal lighting conditions.

	Ball	Goal (yellow)	Goal (blue)	Field
$H_{\max}$	24	100	244	164
$H_{\min}$	343	54	153	97
$S_{\max}$	**100**	**100**	**100**	**100**
$S_{\min}$	69	55	68	68
$V_{\max}$	**100**	**100**	**100**	**100**
$V_{\min}$	13	23	16	18

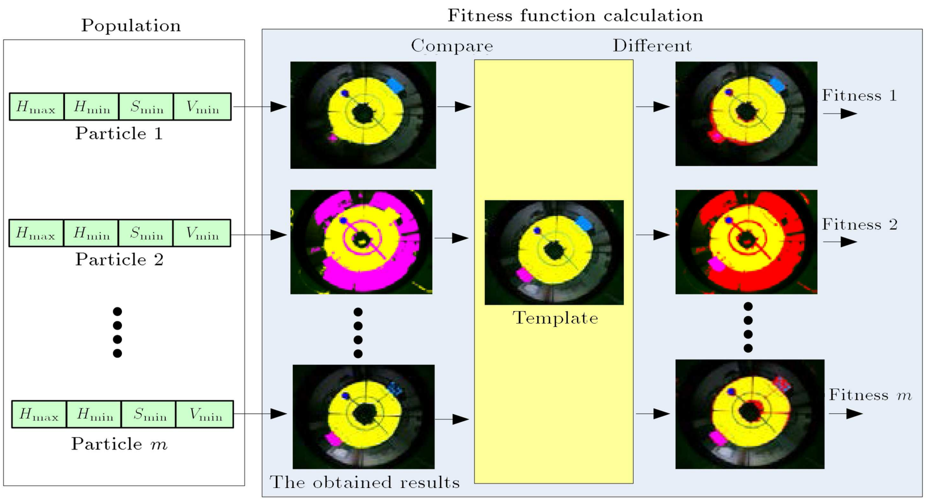


Figure 7. The calculation of the difference among images to get the fitness function assessment result.

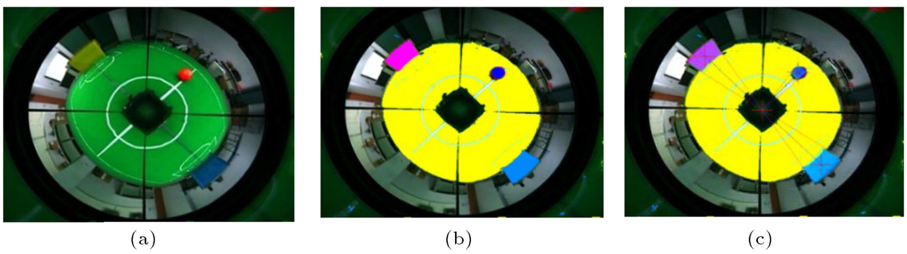
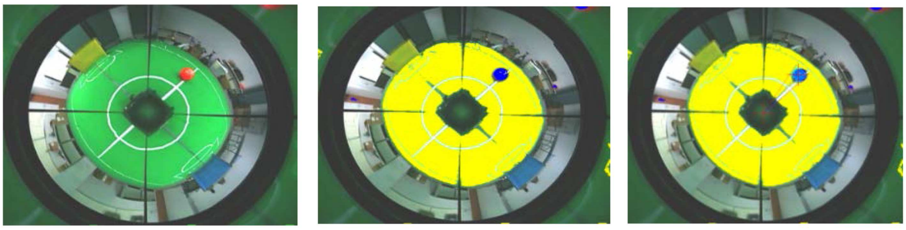
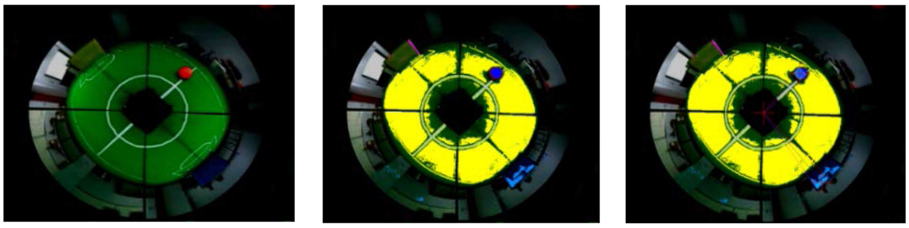


Figure 8. Omnidirectional image under ideal lighting conditions: (a) The original image; (b) the extraction result of target objects; and (c) the recognition result.



(a) (b) (c)

Figure 9. Target objects detection result after lighting conditions change: (a) Brighter lighting condition; (b) the extraction result of the target objects; and (c) the recognition result.



(a) (b) (c)

Figure 10. Target objects detection result after lighting conditions change: (a) Darker lighting condition; (b) the extraction result of the target objects; and (c) the recognition result.

Table 1, we can obtain the extraction results of target objects, such as the ball, the goals and the field, as in Figure 8(b). After confirming the block position of the target objects, from information, such as distance and relative angle of the center point pixel of the acquired image (Figure 8(c)), we can then calculate the actual distance and relative position of the target object in the soccer field.

Since the lighting conditions of the soccer field usually change, along with the game time or game site, usually, when the lighting conditions are changed, the originally setup color-feature model will have difficulty in detecting the target object successfully. Figure 9(a) and Figure 10(a) show, under somehow brighter and darker lighting conditions, cases when the color-feature model of Table 1 is used to undertake target object detection. It is clear that most target objects can no longer be extracted successfully, and the results are as shown in Figure 9(b)-(c) and Figure 10(b)-(c). In the example of Figure 9, only the ball and the field can be successfully detected, and all the blue and yellow gates cannot be detected. Figure 10 is an example of the failed detection of a yellow gate, and the blue gate and field block in this case cannot all be fully acquired.

In order to avoid the influence of lighting condition changes on the vision system of the soccer robot, and the subsequent failure of analysis of the peripheral environment using preset judgment conditions, in this research, we have used the PSO algorithm to set up a color-feature model dynamically. Hence, we can cope with the change in lighting conditions to perform the parameter adjustment of the model. In the experiment,

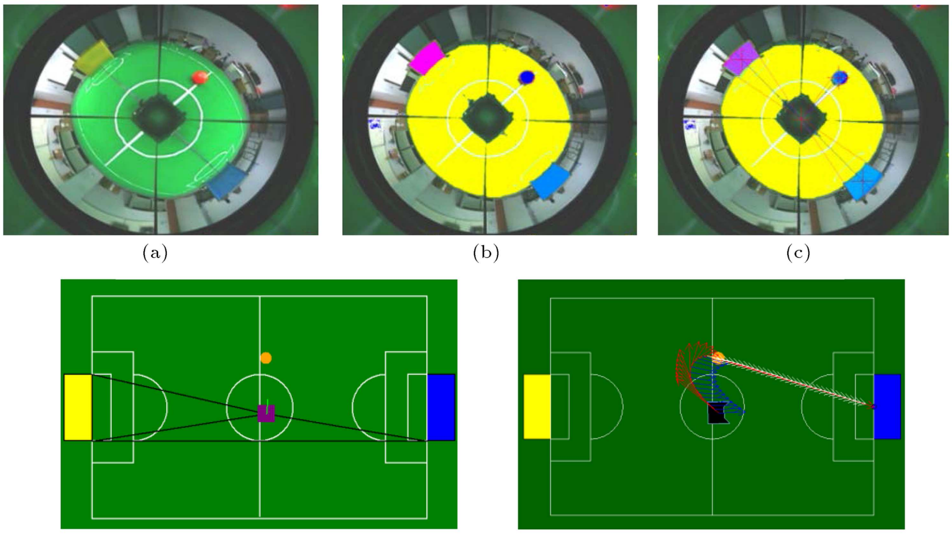
Table 2. The parameter values of the color-feature model obtained under brighter lighting condition.

	Ball	**Goal (yellow)**	**Goal (blue)**	**Field**
$H_{\max}$	74	100	258	150
$H_{\min}$	290	36	180	95
$\boldsymbol{S_{\max}}$	**100**	**100**	**100**	**100**
$S_{\min}$	5	58	46	43
$\boldsymbol{V_{\max}}$	**100**	**100**	**100**	**100**
$V_{\min}$	86	52	41	52

we have set up the number of particles of PSO to be equal to 20, the iteration number = 50, and $c_1 = c_2 = 1.5$.

After the robot and all the target objects on the soccer field are placed in their fixed positions, Table 2 shows the obtained evolutionary color-feature model using PSO under brighter lighting conditions (Figure 11(a)). Through the extraction condition of Table 2, we can successfully detect all the target objects, as shown in Figure 11(b) and (c). After completing the recognition of the target objects, the soccer robot can further use a self-localization algorithm to confirm the relationship, such as relative location and distance between the target objects [16] (Figure 11(d)). Meanwhile, soccer ball shooting is implemented according to the path planning result (Figure 11(e)).

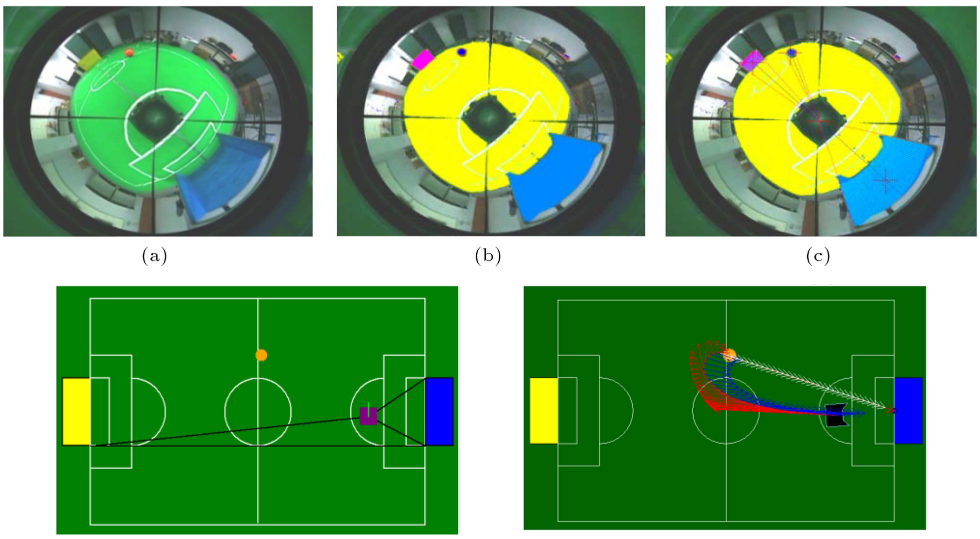
As the robot moves to different locations and under different viewing angles, the image acquired by the omnidirectional camera will change (Figure 12(a)). However, through the extraction condition of Table 2,



(a) (b) (c)

(d) (e)

Figure 11. The extraction and recognition results of target objects using the color model parameters (Table 2) constructed by PSO: (a) Brighter lighting condition; (b) the extraction result of the target objects; (c) the recognition result; (d) the self-localization result; and (e) the path planning result.



(a) (b) (c)

(d) (e)

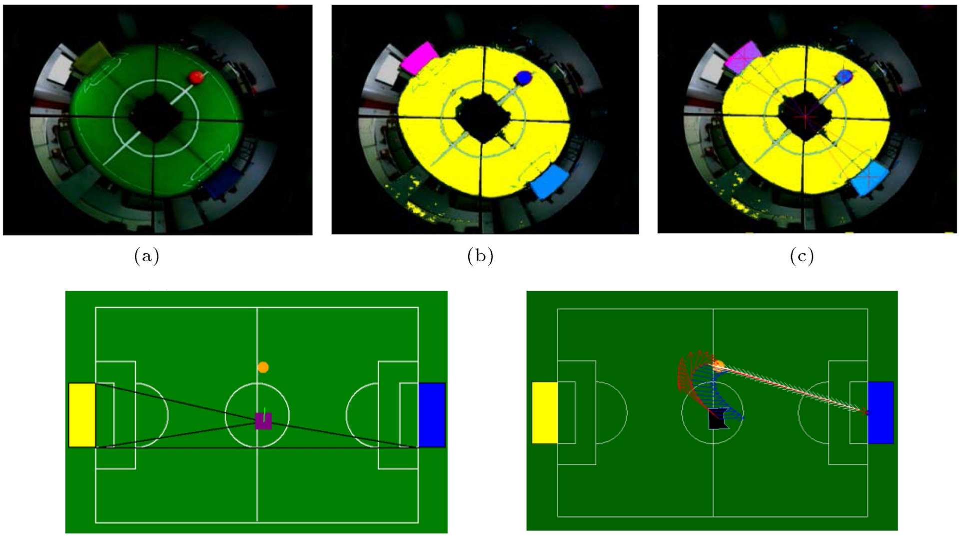
Figure 12. The extraction and recognition results of target objects using Table 2 after robot has changed its position during the walking process: (a) The omnidirectional image obtained at different locations; (b) the extracted result of target objects; (c) the recognition result; (d) the self-localization result; and (e) the path planning result.

we can still detect all the target objects, which are as shown in Figure 12(b)-(c). Figure 12(d) shows the self-localization result, and Figure 12(e) is the path planning result.

Based on the same procedures, we have confirmed the model construction capability of PSO under a darker environment, which is shown in Figure 13(a). The parameter values obtained from the color-feature model are listed in Table 3. Figure 13(b)-(e) show the results of target object extractions, self-localization results, and path planning. Here, we can find that the evolutionary vision system constructed based on PSO,

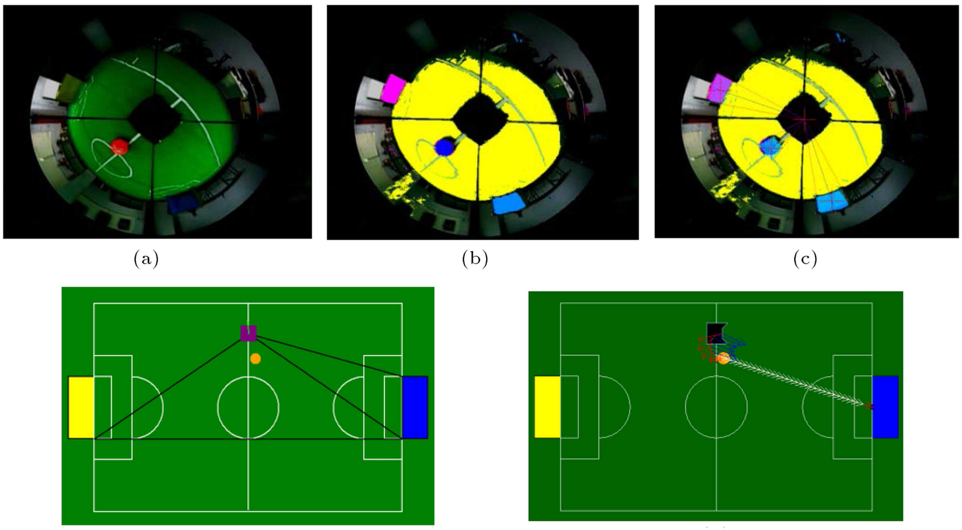
Table 3. The parameter values of the color-feature model obtained under brighter lighting condition.

	Ball	**Goal (yellow)**	**Goal (blue)**	**Field**
$H_{\max}$	48	110	275	143
$H_{\min}$	316	41	220	119
$\boldsymbol{S_{\max}}$	**100**	**100**	**100**	**100**
$S_{\min}$	37	98	98	76
$\boldsymbol{V_{\max}}$	**100**	**100**	**100**	**100**
$V_{\min}$	41	13	1	17



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

Figure 13. The extraction and recognition results of target objects using the color model parameters (Table 3) constructed by PSO: (a) Darker lighting condition; (b) the extraction result of the target objects; (c) the recognition result; (d) the self-localization result; and (e) the path planning result.



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

Figure 14. The extraction and recognition results of target objects using Table 3 after robot has changed its position during the walking process: (a) The omnidirectional image obtained at different locations; (b) the extracted result of target objects; (c) the recognition result; (d) the self-localization result; and (e) the path planning result.

and under different lighting conditions has a very good fitting capability.

Similarly, if the robot is under such a darker lighting condition, even after arbitrary movement, its vision system can still correctly analyze and recognize the acquired omnidirectional images under different viewing angles, as shown in Figure 14.

5. Conclusion

In this paper, a method for the automatic setup of a color-feature model using PSO is introduced. The method can very efficiently accelerate the parameter setup process of the vision system of a FIRA soccer robot. Meanwhile, it can surmount the over-relying issue of the current architecture on lighting conditions when undertaking target object detection. In order to verify the effectiveness of the mentioned method, we have performed tests with different lighting conditions in the experiment. The results show that the parameters can be smoothly adjusted in the vision system of the soccer robot, and the color-feature model applicable to the operational environment at that time can then be set up. In addition, we have also displayed, in this paper, the self-localization and path planning function of a soccer robot after it has successfully detected the target objects. Moreover, the related experimental results are sufficient to explain that the evolutionary vision system design method proposed can indeed be applied in a soccer robot game.

Acknowledgments

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