Automatic Color Detection for MiroSOT Using Quantum-inspired Evolutionary Algorithm

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Abstract. In a MiroSOT robot soccer program, operators manually adjust color setting using global vision system for detecting objects such as robots and a ball. It is a cumbersome and time-consuming operation before the game. Since spectators may make shadows and illumination changes on the pitch, it becomes more difficult to detect colors of the objects. For the convenience of operators, automatic color setting algorithm is needed. In this paper, an automatic color detection algorithm is proposed, in which quantum-inspired evolutionary algorithm is used. The effectiveness of the proposed algorithm is successfully demonstrated in the real robot soccer pitch with five MiroSOT soccer robots.

1 Introduction

As MiroSOT[1][2] is an abbreviation for Micro Robot World Cup Soccer Tournament. Each team consists of three players, one of them is the goalkeeper. To get information about position of individual players and the orange golf ball, the color camera connected to the computer is used and it is called global vision system. To identify the ball, and players position, color region of interest have to be defined previously. Generally, lookup table is used in MiroSOT. Using lookup table, region of interest could be obtained by back projection to original images. The information about position and orientation of each player could be obtained by color information only. So, many participants have tried to make their own novel color patch attached at top of each players. Quadrilateral color path or oblique color path is used in general. However, as two or more robots are closer to each other, color identification is much harder. To overcome this problem, round patches for team color and peripheral round patches for ID of each player in the same team are used[3]. Also, there has been an approach to color patch design called Soty-Segment color detection in which each player could be identified by using only team color, direction color and position color[4]. However, these two methods assume that lookup table related to region of interest could be unchangeable during match. In real world, regions of interest vary every frame due to variation of environments such as illumination, shading, shadows, and noise so that it is hard to get desired lookup table in every frame.

In this paper, we propose an approach to automatic color detection[5] of the ball, team color and ID color based on quantum-inspired evolutionary algorithm (QEA). As quantum-inspired evolutionary algorithm[6][7] provides one solution of the problem which is difficult to solve mathematically, the goal of this algorithm is to find the optimal value that maximizes a fitness function. Before using quantum-inspired evolutionary algorithm, which parameter would be used and how fitness could be defined are important issues. The number of blobs and portion of noise in global image could be considered for defining fitness function. In experiment, this proposal method is applied to arbitrary image in which blobs related to the ball and robots are detected and noise is removed well.

This paper is organized as follows. In Section 2, quantum-inspired evolutionary algorithm is described briefly. In Section 3, automatic color detection method is presented. In Section 4, the experimental result is presented and finally conclusions and further work follow in Section 5.

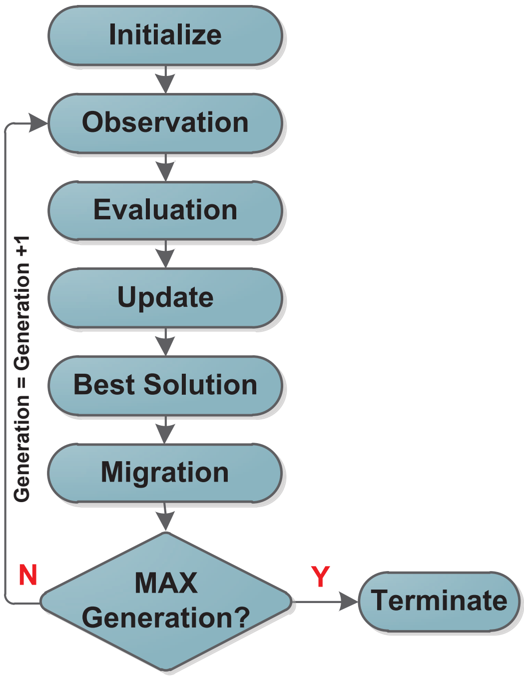


Fig. 1. Quantum-inspired evolutionary algorithm flow

2 Quantum-inspired Evolutionary Algorithm

Quantum-inspired evolutionary algorithm[8][9] is the algorithm to solve complex problem mathematically by iteration. All results could not guarantee optimal solution but results could be near to optimal solution. This algorithm is based on the concept of quantum computing, such as a quantum bit and superposition of states. The candidate solutions that have lower fitness compared other solution in same generation is filtered out. The candidate solutions that have higher fitness are inherited to next generation consistently so that candidate solutions could be close to optimal solution gradually. To apply this concept as search problem, candidate solutions are generated by Q-bits having a probability being "0" or "1". The Q-bit individual size varies with problems. Each candidate solutions by observing the state of Q-bit individuals have to be evaluated how the solution is fitted. The solution having higher fitness could have more probability for survival in next generation. Q-bit individuals are updated by Q-gate so that new Q-bit individuals are generated. After update, the best solution is choose and migration is implemented with some migration condition. The more generation is increased, the more probability that optimal solution is in current Q-bit individual set is increased.

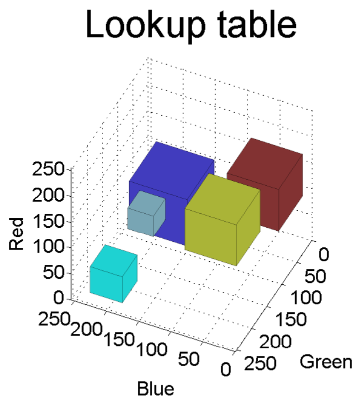


Fig. 2. Lookup table example with five cubes

In this paper, automatic color setting algorithm for MiroSOT is implemented by using quantum-inspired evolutionary algorithm. In general, color ranges for the ball and each team member are attained using global vision system. As this work is very cumbersome, automatic color setting is required in MiroSOT. Prior to get color ranges automatically, color ranges interested are needed among RGB color model. RGB model has Cartesian coordinates system. In this system, multiple cubes appropriate to regions of interest have to be found in the sense that combination of various colors could be recognized as one object. To represent these cubes more simply, the number of cubes is restricted to 5 cubes. This concept is plotted in Fig. 2 diagrammatically. Pixels in cubes mean region of interest.

To find optimal central point and side length in each cube, quantum-inspired evolutionary algorithm is used. Center points and side length for each cube are represented in array of 8 bits so that each parameter, binary string 00000000 would be evaluated to 0, and 11111111 to 255. Each solution could be represented in array of 32 bits. The total number of Q-bit individuals is restricted to 30. After generating solutions randomly, each of them has to be evaluated by some criteria. Criteria for determining fitness are the number of blobs, noise and so on. During each successive generation, some best solutions have to be migrated in next generation. Solutions that have higher fitness are more likely to be migrated. In QEA, a migration is simply defined as the process of copying best solution to another.

3 Automatic Color Detection Algorithm Using QEA

Fig. 3 shows the flow graph of the proposed automatic color detection algorithm. In this figure, the evaluation part is the key-point for the automatic color detection.

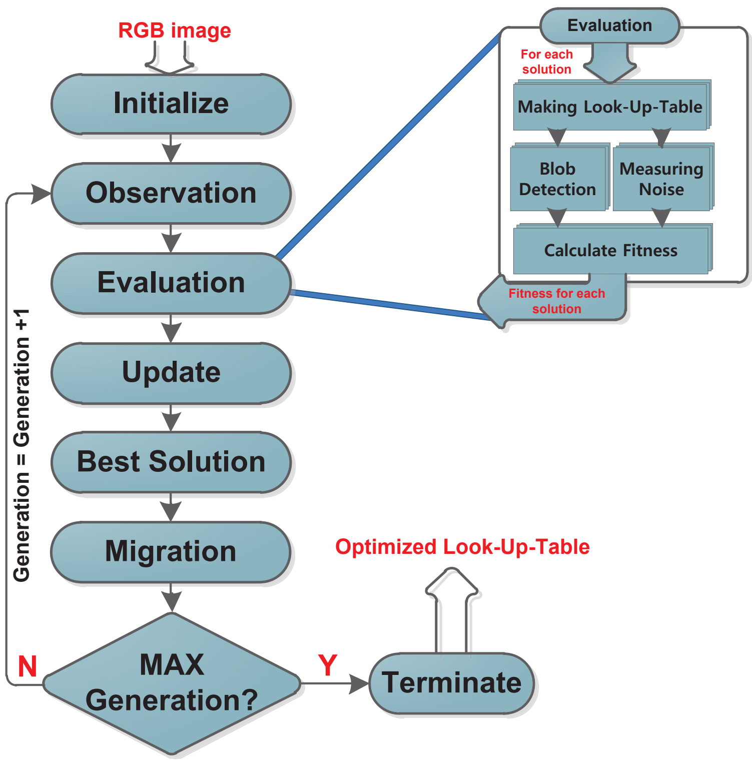


Fig. 3. The flow graph of the automatic color detection algorithm using QEA

In this paper, the fitness function is implemented to evaluate each solution. The fitness function consists of two phases, which are blob detection and noise evaluation. Blob detection is conducted using the matched image with lookup table made by each solution. The number of detected blobs means the number of objects to be detected. After blob detection, noise evaluation is followed. Noise is evaluated by counting pixels unlinked to the detected blobs.

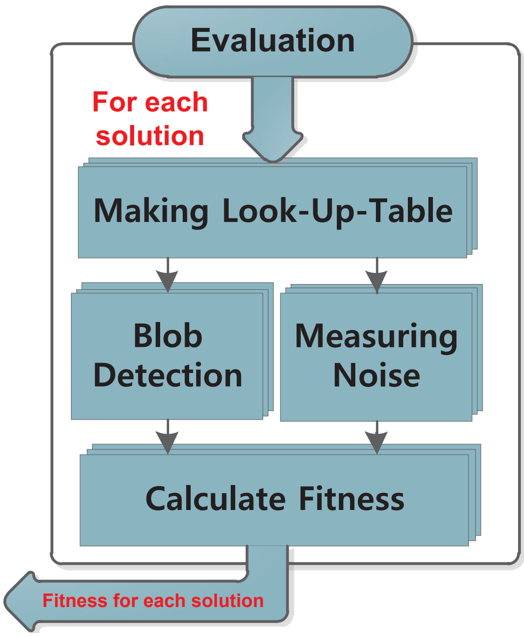


Fig. 4. Evaluation function for each solution in the proposed algorithm

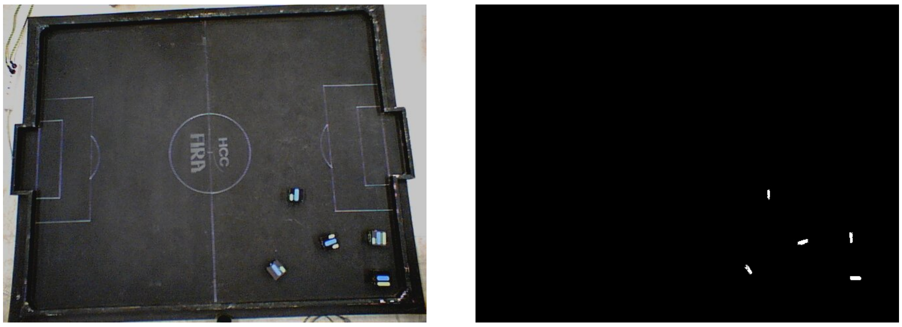
Fig. 4 shows an internal structure of the evaluation function in the proposed algorithm. The fitness function of each blob is

$$f(k, i) = f_B(k, i) + f_N(k, i) \tag{1}$$

where f_B is the fitness function of the number of blobs; f_N the fitness function of noise; k the generation number; i the number of solution.

3.1 Blob Detection

The blob means a mass in a image matched with the lookup table being generated by each solution. By using the linear searching method, blobs are easily detected. An objective of using the blob number in evaluation function is to induce the result to detect target objects such as the ball and robots. The blob number means the number of the target objects.



(a) RGB image source (b) The five blobs of MiroSOT team ID

Fig. 5. Blob example of MiroSOT team patches

Fig. 5 shows example to extract five blobs from RGB image sources. Using the recursive grass-fire algorithm[10], each of these blobs is labeled. After labeling each blob, the number of blobs is directly acquired. For quantum-inspired evolutionary algorithm, the fitness of the number of blobs is computed from

$$f_B(k,i) = w_B \times \left| \frac{N_B(k,i) - N_O}{N_O} \right| \tag{2}$$

where w_B is the weight factor of the number of blobs; N_B the number of blobs; N_O the number of objects to detect. In this paper, w_B is empirically defined.

3.2 Noise Evaluation

Noise is an essential criterion to automatically detect colors. In this paper, noise is evaluated by counting pixels at the image, which is matched with lookup table except blob pixels. For quantum-inspired evolutionary algorithm, the fitness of the number of noise pixels is calculated from

$$f_N(k,i) = w_N \times \frac{N_N(k,i)}{Max_N} \tag{3}$$

where w_N is the weight factor of the number of noise pixels; N_N the number of noise pixels; Max_N the maximum number of noise pixels. Max_N and w_N are heuristically defined.

4 Experiment

The proposed algorithm was tested with real MiroSOT soccer robot system. Experimental environments were Gentoo OS, Intel i5 3.3GHz Dual-core processor, NVIDIA GTX 560 GPU and 6GB RAM. As shown in Fig. 6, the experiments were carried out with five different images to automatically find team colors. For the experiments, the fitness parameters were set as the object number = 5, w_B

= 0.65, w_N = 0.35, and Max_N = 10,000. Futhermore, quantum-inspired evolutionary algorithm parameters were set as 2,000 generations and Q-bit individual size = 30.

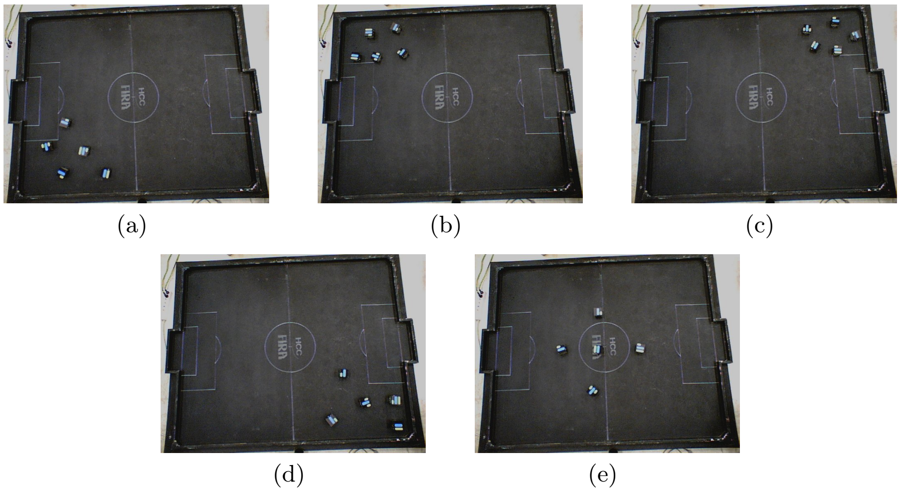


Fig. 6. Experiment images having different positions of robots

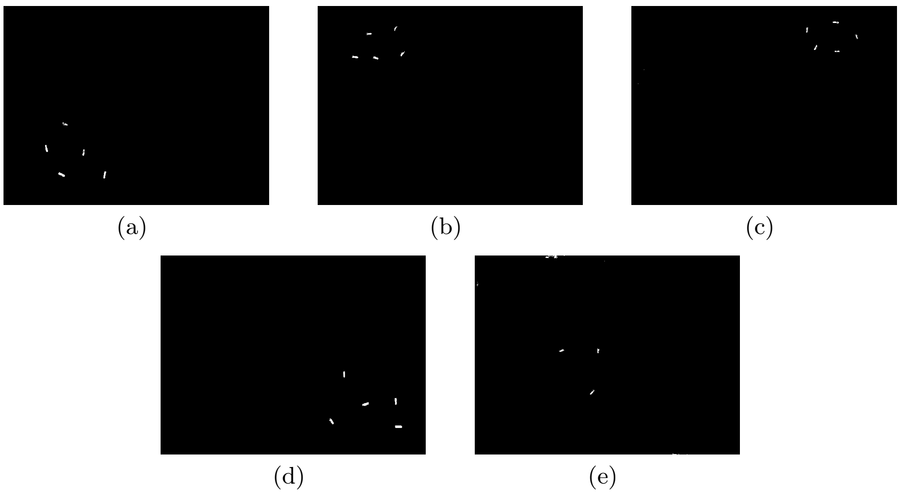


Fig. 7. Results of the automatic color detection - at 2,000 generations; a Q-bit individual size of 30

In Fig. 7, the automatic color detection results are shown.These experiment results show that the effectiveness of the proposed algorithm was successfully demonstrated for automatic color detection. Furthermore, Table 1 shows that the results are more accurate as the generation increases. However, Table 1 also shows that the proposed algorithm takes a long time due to the image processing for each solution.

Table 1. Experiment results of different generation numbers

Generation	Avg. N_B	Avg. N_N	Computing Time (min)	Computing Time Std. (min)
100	1.8	159162.2	1.0908	0.1099
500	4	79.4	4.6683	0.3259
1,000	4	71.6	9.4193	0.4494
2,000	4.6	5.8	18.4007	0.4664

Fig. 8 shows the best fitness of each generation. As the generation increases, the fitness values converged to zero.

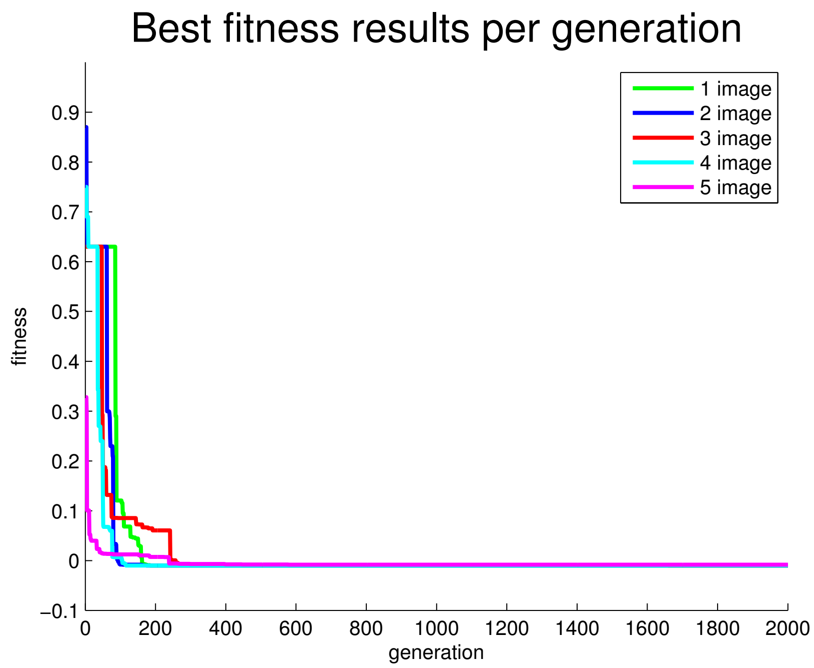


Fig. 8. Best fitness results of the automatic color detection - at 2,000 generations; a Q-bit individual size of 30

5 Conclusion and Future Work

This paper proposed automatic color detection for MiroSOT using quantum-inspired evolutionary algorithm. In MiroSOT, lookup table is necessary to identify team color, ID color and a balls color. According to the defined lookup table, original image is back-projected so that team color, ID color and balls color could be identified. However, color can be viewed differently by variation of illumination, shadow and noise. So, depending on pre-defined lookup table entirely has a limitation. In this paper, lookup table has to be found without prior knowledge to deal with these variations. In RGB Cartesian coordinate system, pixels which are inside five cubes were defined as regions of interest to avoid over-fitting problems. Using lookup table represented by combination of these cubes, an original image was back-projected to a binary image in which fitness is defined whether the number of blobs is the same as actual number of blobs. In addition, noise was considered to define fitness function. In experiment, the proposed method was applied to arbitrary image in which blobs related to the ball and robots were detected and noise was removed well.

However, there is a problem that computation time required to perform quantum-inspired evolutionary algorithm takes a long time. At every generation in quantum-inspired evolutionary algorithm, lookup table should be generated and blob detection be performed. Thus, this algorithm could not be applied to real-time system such as MiroSOT. This problem would be solved by using GPU from a hardware perspective. Also, there is an assumption that positions of each player and the ball are independent of positions of those in previous frame. Actually, positions in current frame are dependent on those in previous frame. Thus, applying Bayes rule to relate between previous and current frames could be a good solution to processing more rapidly.

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