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Abstract: As the robot soccer system becomes stabilized, it has been used as an educational platform with which various topics on mobile robotics can be taught. As one of key topics in the education of mobile robotics is computational intelligence-based navigation, this paper proposes a multi-objective population-based incremental learning (MOPBIL) algorithm to obtain the fuzzy path planner for optimal path to the ball, minimizing three objectives such as elapsed time, heading direction and posture angle errors in a robot soccer system. MOPBIL employs the probabilistic mechanism, which generates new population using probability vectors. As the probability vectors are updated by referring to nondominated solutions, population converges to Pareto-optimal solution set. Simulation and experiment results show the effectiveness of the proposed MOPBIL from the viewpoint of the proximity to the Pareto-optimal set, size of the dominated space, coverage of two sets and diversity metric. By implementing each of the solutions into the educational platform, it can be educated how multi-objective optimization is realized in the real-world problem.

Evolutionary Multi-Objective Optimization in Robot Soccer System for Education

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1. Introduction

A knowledge should be educated to the next generation otherwise it is scientifically meaningless. In this sense, many researchers have been trying to find more effective education method. It was reported that a hardware experiment course using microcomputer system and its associated software was much more effective in education [1]. The positive effect on education was also reported when using specific experiment tools and products [2, 3]. Advanced programs have been provided for students to learn the methodology of problem-solving in optimization, learning and design on real-world problems [4, 5]. Robot soccer system is well known as

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one of educational platform for the experiment educational program, which is useful in educating computational intelligence and integration technology of control algorithm, wireless communication, computer vision, software system, navigation, etc [6, 7].

Among various topics, this paper deals with the navigation in robot soccer based on fuzzy inference system and multi-objective evolutionary optimization. Traditional navigation method calculates simple shortest paths by considering the composition of rotation, circular and straight motions in path planning [8]. As a recent approach, fuzzy path planner based on fuzzy inference system has become an important technique in navigation [9]. It reduces the time of system design, simplifies the implementation complexity and improves the performance. However, deriving the fuzzy rule is a challenging problem because it is time consuming, difficult and dependent on an expert's knowledge. In order to overcome this problem, evolutionary fuzzy path planners were presented using unit-vector field [10–12]. There are lot of related research on navigation by using fuzzy logic and evolutionary computation [13–17]. Most of these evolutionary schemes are optimized for a better fitness, represented as a single objective optimization problem.

In real-world problems, however, several objectives are inherently involved at the same time, which are known as multi-objective optimization (MOP) problems. Navigation problem also has multiple objectives such as shortest path and time, minimum energy, etc. To satisfy these objectives simultaneously, multi-objective evolutionary algorithm (MOEA) is needed, which uses a population to search for Pareto optimal solution set.

The growing interest in highly complex search space has spurred the growth of MOEA [18, 19]. The nondominated sorting genetic algorithm (NSGA) was presented [20] and improved as NSGA-II, which is a strong elitist method with a mechanism to maintain diversity efficiently using nondominated sorting and crowding distance assignment [21]. Also, population-based incremental learning (PBIL) for MOP was presented with updating schemes of probability vectors [22], which shows better performance than the existing representative MOEAs on multi-objective numerical test functions such as ZDT and DTLZ functions [23, 24]. However, the PBIL is difficult to maintain nondominated solutions in MOP because it selects only one best solution to update the probability vectors and thus solutions may cluster over one point and fall into local optimum.

In order to solve the problem of the PBIL for MOP, this paper proposes a multi-objective population-based incremental learning (MOPBIL) algorithm, which provides a wider search space by randomly selecting nondominated solutions in archive when each element in probability vector gets updated. Due to good balance between exploration and exploitation, probabilistic representation guarantees the faster convergence. In addition, calculation of nearest neighbor distance is employed as a method for maintaining diversity to reduce the size of memory and to simply measure the distribution of solutions. The performance of MOPBIL algorithm is verified through both simulations and experiments, where MOPBIL is applied to optimize a fuzzy path planner with three minimization objectives such as elapsed time, heading direction error and posture angle error from testing initial positions to the ball in a robot soccer system.

This paper is organized as follows. Section II presents a brief overview of robot soccer system. Section III describes the fuzzy path planner and proposes the MOPBIL. In Section IV, both simulation and experiment results demonstrate the effectiveness of MOPBIL. Finally, concluding remarks follow in Section V.

2. Robot Soccer System for Education

There are two types of robot soccer system for FIRA RoboWorld Cup: global-vision based one for MiroSot and local-vision based one for HuroCup and RoboSot [25]. In the former system, a host computer decides current situation and sends locomotion command to each robot wirelessly by checking the field image from a camera located on the top of field and calculating a strategy. In other words, multi-robot cooperation strategy is provided by the external host computer. In contrast, the latter system requires camera, controller and embedded computer for each robot to calculate its own location by using landmarks located on the field and to cooperate with each other. If the robot is developed as a stand-alone system in which all functionalities are installed, it takes longer time to process images and identify the game situation.

In general, the global-vision based robot soccer system, also known as micro-robot soccer system, is suitable for education because it is easy to install and test control algorithm, computer vision, communication and so on, as shown Figure 1(a). The main advantage of this system is that a user can control the overall system from one host computer. Since the system covers all fields in robotics, various educational effects can be expected [6]. The system consists of robots, a host computer, an overhead vision camera and a wireless communication system. It is used as a test bed for multi-agent systems and multi-robot cooperation systems. Its complexity comes from the cooperation of home team robots, the competition against opponent team robots, and the fast and precise control of each robot while tracking the ball (Figure 1(b)).

In the early stage, the research was mainly focused on vision process, motor control and wireless communication. In order to develop it into an efficient educational platform, the first challenge was to develop a reliable vision processing system. Vision processing algorithms were immensely advanced through FIRA RoboWorld Cup [25]. At the same time, the functions of hardware including camera and frame-grabber were enormously improved. As the stability of vision processing enhanced, education and research issues in the micro-robot soccer system were naturally extended to navigation, cooperation, strategies and so on.

Recently, the micro-robot soccer system has been developed as ubiquitous robot system viewpoint where strategy module, vision camera and soccer robot possess the role of software robot, embedded robot and mobile robot, respectively [26]. Since it activates research motivations though competition against other teams, higher educational effect can be expected. It covers wide education and research topics, and it can be used as an education and research platform in both university and research institutes. In addition, the value of the system as an educational platform for young students has been verified through Robot Olympiad, which is organized by International Robot Olympiad Committee (IROC) [27].

Figure 2 shows micro-robot and its internal modular structure. Micro-robot has two driving wheels and its size is 7.5 cm × 7.5 cm × 7.5 cm. The overall modular structure is mainly divided into micro-controller module, motor driver module, communication module and power module. Once the velocity command for two wheels is received from the communication module through a radio frequency transmitter, this information is sent to the micro-controller module

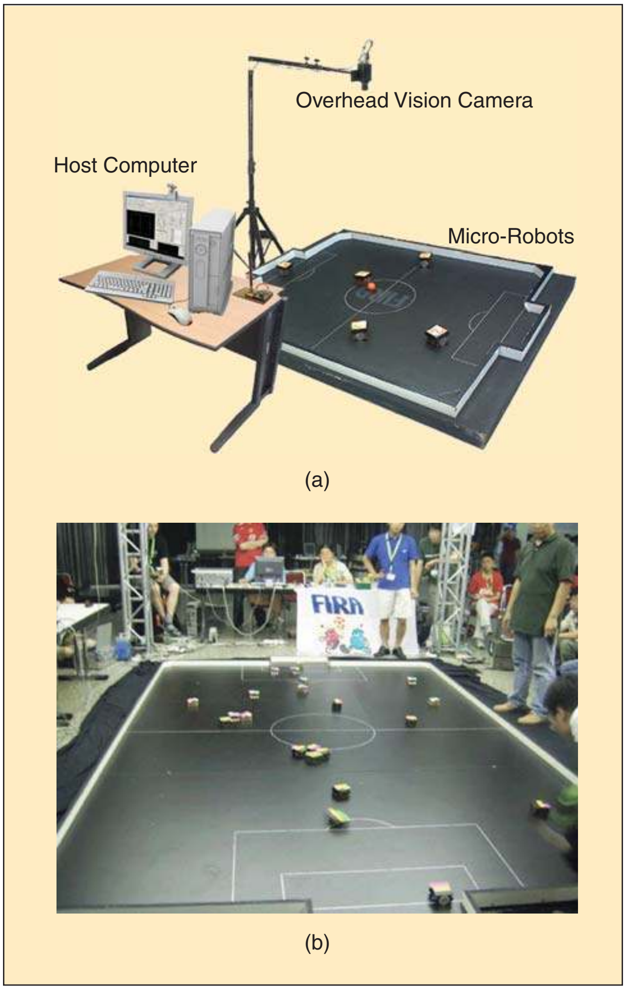

FIGURE 1 (a) Micro-robot soccer system and (b) robot soccer competition.

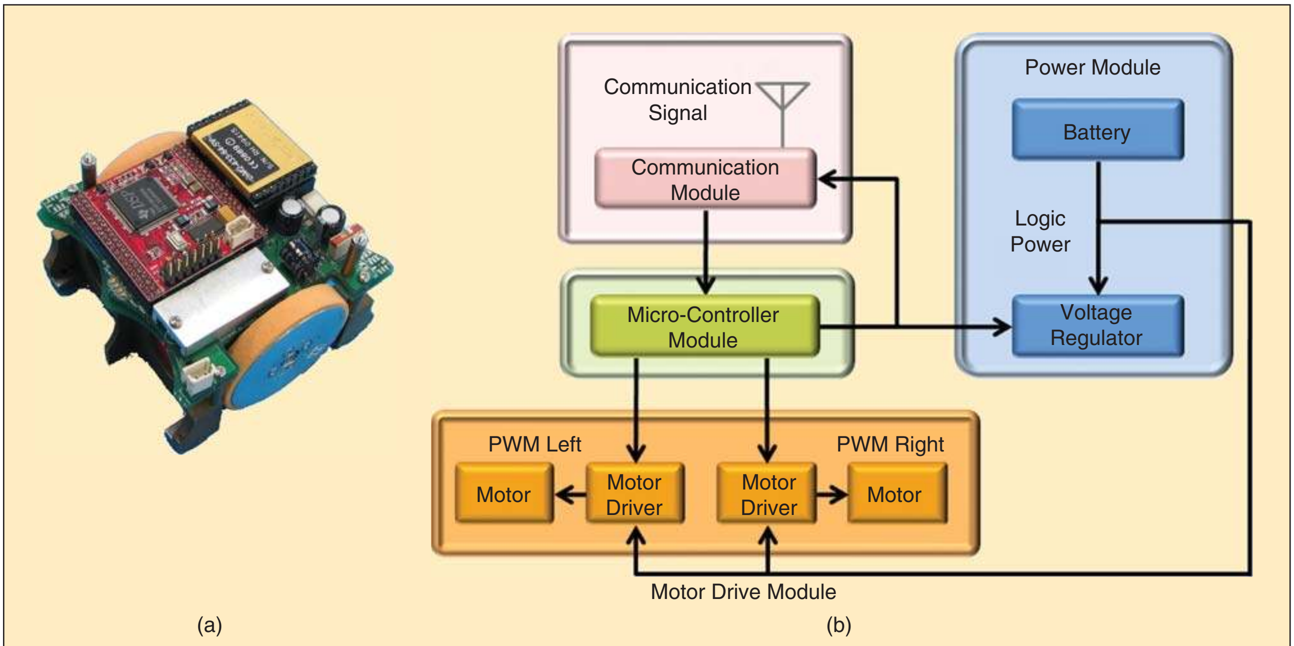

FIGURE 2 (a) Micro-robot and (b) its internal modular structure.

In addition, the value of the system as an educational platform for young students has been verified through Robot Olympiad, which is organized by International Robot Olympiad Committee (IROC).

to control the velocity of two wheels. The motor driver module then drives two DC motors where the power module generates operating voltage from battery using voltage regulator [28].

Vision camera estimates the posture information using color patch located on the top of robot and transmits it to the host computer [29]. Depending on the size of field, one or more cameras can be used to capture a whole field image. Once the host computer receives the vision images, it runs a strategy routine to calculate the velocity of each robot. The strategy routine is to select a proper action for each robot considering the game situation. Note that the processing rate of controller camera limits the sampling time of controller because the localization of robot is made only by the vision camera. As an example, if camera captures an image with the rate of 110 frames/sec, the sampling time is set to be 9.1 ms. In addition, the system must consider measurement errors, which are accumulated from the time delay of vision camera or inaccuracy of its processed images.

The screenshot of micro-robot soccer GUI is shown in Figure 3. In the field image located on the left side, the results of vision process including the position and direction of robots, position of ball, information related to opponent team robots are displayed in real-time. This image can be transformed to simulation mode to verify strategies. On the right side, there is a user interface to change the role and task of robots according to game situation. It indicates the information related to the location and task of selected robot, where the control parameter settings can be modified as well. The graphs, which monitor the processing time of vision, strategy and the system, are located at the bottom.

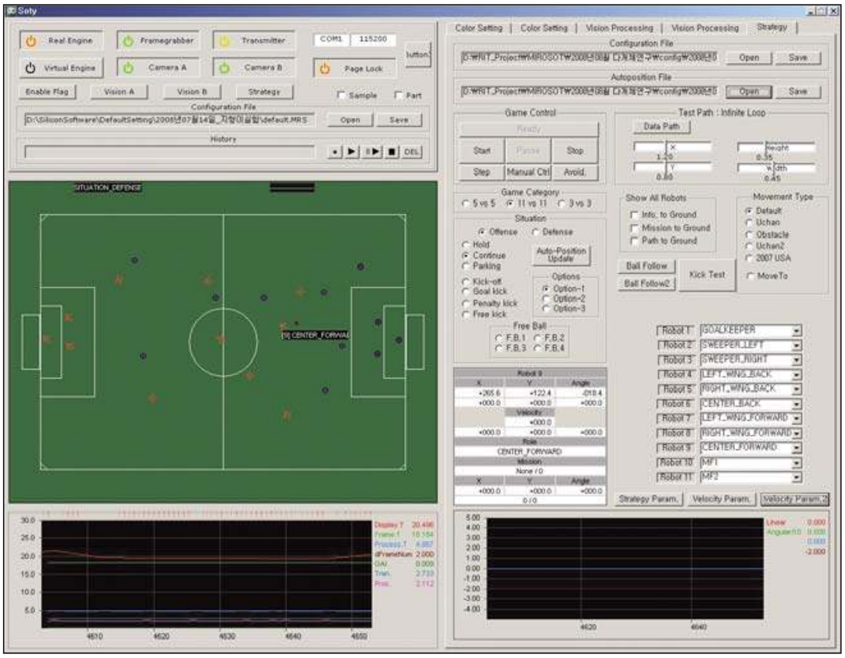

FIGURE 3 Screenshot of micro-robot soccer GUI.

Students can learn related technologies by programming the game strategies and verifying the performance of robots by themselves [6]. However, young students have limitations in high-level programming for developing game strategies. Considering this problem, an educational program was developed for them, which provides graphical user interfaces to set global-vision camera, to test communication with each robot, and to select both position and movement of robot [30]. They can easily create their own strategy in simulation and then physically test it using real robots.

TABLE 1 Example of fuzzy inference rules for heading angle.

ϕ \ ρ	VN	AN	SN	MD	SF	AF	VF
VS	179	3	206	112	306	31	102
LS	56	210	110	228	251	168	94
SS	57	240	224	228	319	292	273
MD	253	143	242	240	295	164	155
SL	28	217	213	349	332	265	277
AL	43	270	326	280	261	5	249
VL	228	10	357	56	271	163	124

(VN: Very Near, AN: Average Near, SN: Somewhat Near, MD: Medium, SF: Somewhat Far, AF: Average Far, VF: Very Far, VS: Very Small, AS: Average Small, SS: Somewhat Small, MD: Medium, SL: Somewhat Large, AL: Average Large, VL: Very Large).

3. Evolutionary Multi-Objective Optimization in Robot Soccer System

As one of educational topics in mobile robotics using a robot soccer system, computational intelligence-based navigation is considered, which ensures proper trajectories and navigation time to the ball. To reduce the time of system design, to simplify the implementation complexity and to improve the performance, fuzzy inference system is employed for the path planner. However, derivation of fuzzy rule is a challenging problem because it is time consuming, difficult and dependent on an expert's knowledge. Moreover, in the navigation problem of robot soccer several objectives such as elapsed time, heading angle error and posture angle error and so on, should be considered at the same time. To solve these problems, multi-objective population-based incremental learning (MOPBIL) algorithm is proposed to obtain the fuzzy path planner for an optimal path to the ball, minimizing those objectives.

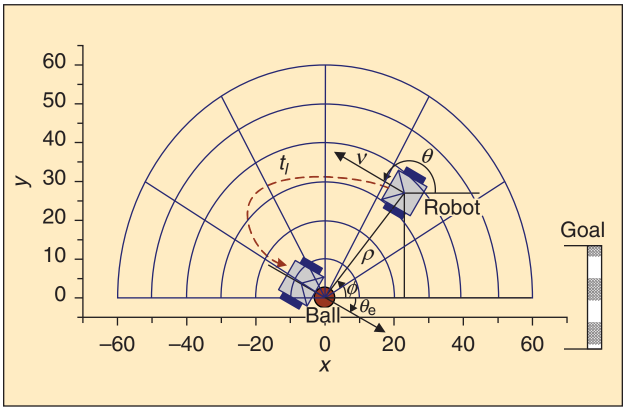

FIGURE 4 Localization variables in robot soccer system.

3.1. Evolutionary Approach for Fuzzy Path Planning

Fuzzy navigation system is composed of two modules: fuzzy path planner and fuzzy path following controller [31]. The main role of fuzzy path planner is to generate a desired path from the current posture to the ball position. The optimality of paths are measured by various criteria along with constraints. By assuming the fuzzy path following controller adequately tracks the desired heading angle, the main focus becomes the design of the fuzzy path planner.

Procedure MOPBIL
Begin
    $t \leftarrow 0$
i) initialize probability vectors (PVs)
    while (**not** termination condition) **do**
    begin
        $t \leftarrow t + 1$
ii) generate binary solutions by the probability of PVs
iii) decode to real number and evaluate
iv) select nondominated solutions in the union set of the population and old archive set
v) fill the archive from the selected nondominated solutions
vi) update PVs referring to the solutions in the archive
    end
end

FIGURE 5 Overall procedure of MOPBIL.

The fuzzy path planner is designed first by fuzzifying the information describing a relative position of soccer robot with respect to the ball. The fuzzified information becomes the input of fuzzy rule set in Table 1, where the consequent parts are represented by real numbers in between 0 and 360. The fuzzy inputs are used to discretize the map of the environment as shown in Figure 4. In the figure, the origin is the location of the ball, ρ is the distance between robot and ball, φ is the angle from x-axis to the location of robot, v is the velocity of robot, t_l is the elapsed time, θ is the heading angle and θ_e is the heading angle error at the moment of kicking the ball or at the last moment of time limit. Note that (ρ, φ) represents the posture of robot. By the fuzzy rule set, an appropriate heading angle ($0° \sim 360°$) is determined corresponding to each input in a univector field [32, 10]. Inputs are constrained to $0 \text{ cm} \leq \rho \leq 60 \text{ cm}$ and $0° \leq \varphi \leq 180°$ (due to geometrical symmetry). As membership functions, standard triangular ones are employed and seven set fuzzy input windows for distance (ρ) and angle (φ), respectively, are used to obtain the membership values of the distance and angle to the fuzzy set (VN $\sim$ VF and VS $\sim$ VL).

The key objectives of path planning in robot soccer are that robot should approach to the ball as soon as possible and kick the ball accurately. Elapsed time during the movement should be minimized to meet the former objective, whereas drift errors such as heading angle error and posture angle error should be minimized for the latter objective.

In the case of single-objective evolutionary algorithm, the fitness of solution is evaluated by summing up each of fitness values for those objectives. However, multi-objective evolutionary algorithm is more suitable for satisfying those objectives simultaneously because they conflict with each other. For example, there exists no solution, which satisfies both fastest movement and highest accuracy simultaneously. Fitness functions in a multi-objective optimization problem of path planning are defined as follows:

$$f_1 = K_t \cdot t_l \quad (1)$$
$$f_2 = K_\theta \cdot |\theta_e| \quad (2)$$
$$f_3 = K_\varphi \cdot |\pi - \varphi|, \quad (3)$$

where f_1, f_2 and f_3 correspond to the fitness function of elapsed time, heading angle error and posture angle error, respectively. K_t, K_θ and K_φ are constants and $|\pi - \varphi|$ is the posture angle error at the moment of kicking the ball or at the last moment of time limit. Note that once the value of posture angle error (f_3) gets decreased, the robot has more

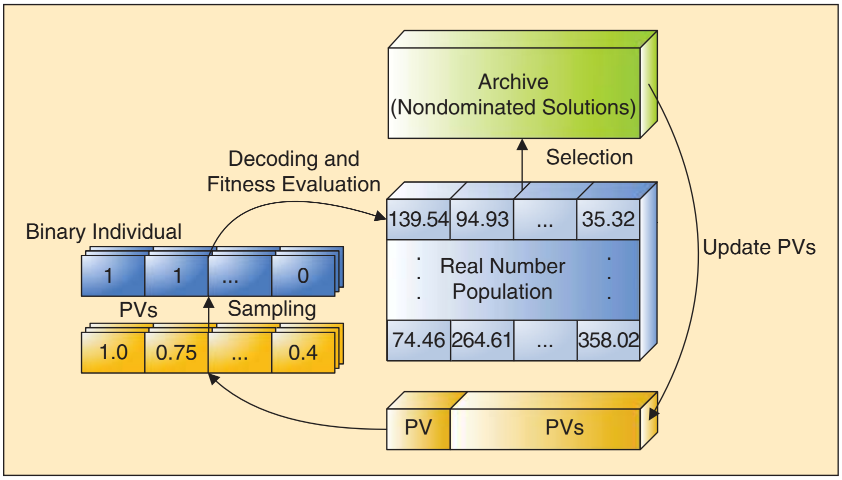

FIGURE 6 Overall structure of MOPBIL.

found and temporarily saved to search for the next nondominated front. This procedure is repeated until all individuals are ranked. For the diversity maintenance, the normalized crowding distance calculation estimates the density of each individual. This density information is utilized to select individuals in the population for the next generation. The crowding distance of an individual refers to the average side length of the cuboid that has the vertices of the nearest neighbors.

3.2. Multi-Objective Population-Based Incremental Learning (MOPBIL) Algorithm

chance to traverse the pitch through the left-side from the ball and the possibility of kicking the ball accurately towards the goal gets increased.

Multi-objective evolutionary algorithm is needed to evaluate the fitness of individual solution of fuzzy path planner using robot soccer system, where two-dimensional rule base, as shown in Table 1, for fuzzy inference is encoded as a chromosome. As one of state of the art MOEAs, NSGA-II is selected for comparison with the proposed one in the next section. NSGA-II was developed with the main schemes of fast nondominated sorting and crowding distance calculation [21]. The fast nondominated sorting procedure for the elitism is as follows: nondominated front is

Multi-objective population-based incremental learning (MOPBIL) algorithm is proposed. The procedure and overall structure of MOPBIL are shown in Figures 5 and 6, respectively. Each step of the procedure is described in the following.

i) The elements of probability vectors (PVs) are initialized to '0.5'.
ii) Binary solutions are generated according to the probabilities in PVs. In other words, one binary solution is formed by selecting either '0' or '1' for each bit using the corresponding probability of PV. PV in Figure 6 represents the probability that 1 is to be generated.

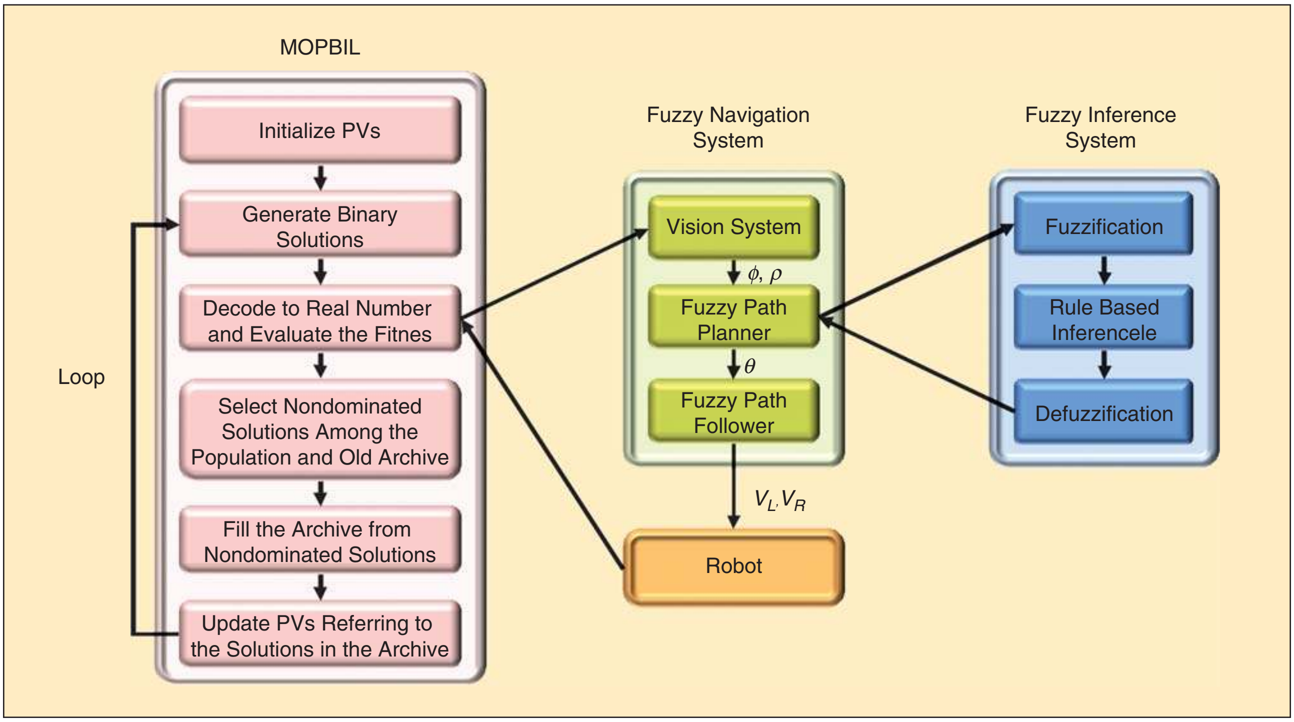

FIGURE 7 Proposed MOPBIL for fuzzy path planning in robot soccer system.

iii) In the case of real number application, generated solutions are decoded to real number and evaluated by fitness measure.

iv) The nondominated solutions are selected from the union set of current population and old archive set. They form the current archive set. If the number of nondominated solutions exceeds the maximum archive size, some solutions having smaller 'nearest neighbor distance' are truncated. Smaller value of nearest neighbor distance represents that the solutions are clustered in a particular region. The nearest neighbor distance, D_n , of i^{th} solution is defined as follows:

As one of educational topics in mobile robotics using a robot soccer system, computational intelligence-based navigation is considered, which ensures proper trajectories and navigation time to the ball.

$$D_n = \min_{1 \le j \le N} \left(\sum_{k=1}^{M} \sqrt{(f_i^k - f_j^k)^2} \right), \tag{4}$$

where N is the population size, M is the number of objectives, f_i^k is the fitness value of k^{th} objective of i^{th} solution and f_j^k is the fitness value of k^{th} objective of j^{th} solution. If a certain solution has several same values of D_n , any value among several values of D_n is chosen. The conventional method, which uses an adaptive grid method to measure the distribution of solutions, requires extra memory space to store these grid information. However, when the nearest neighbor distance method is used, this extra memory space is unnecessary.

vi) PVs are updated by referring to the solutions in the archive. Update law is given as follows [33]

$$P_i^{new} = P_i^{old} \cdot (1 - LR) + b_i \cdot LR, \tag{5}$$

TABLE 2 Parameter setting of NSGA-II and MOPBIL.

ALGORITHMS	PARAMETERS	VALUES
NSGA-II	POPULATION SIZE (N)	20
	NUMBER OF GENERATIONS	2,000
	MUTATION PROBABILITY (p_m)	0.1
MOPBIL	POPULATION SIZE (N)	20
	NUMBER OF GENERATIONS	2,000
	NUMBER OF PROBABILITY VECTORS	49
	MAX. ARCHIVE SIZE	20
	LEARNING RATE (LR)	0.1
	AMOUNT OF SHIFT MUTATION (ms)	0.2
	MUTATION PROBABILITY (p_m)	0.06
	K_t, K_θ, K_ϕ	1

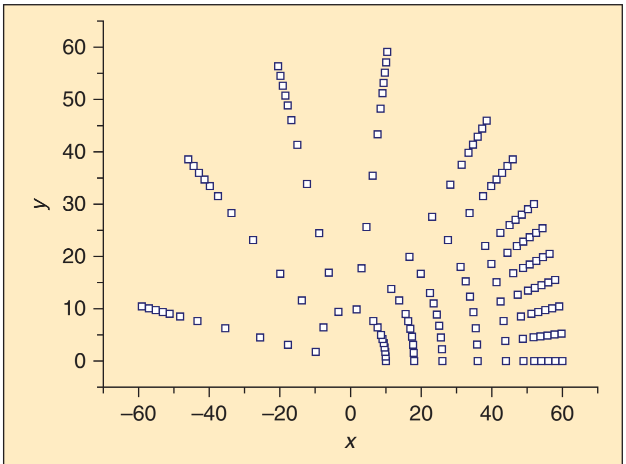

FIGURE 8 143 training points in simulation.

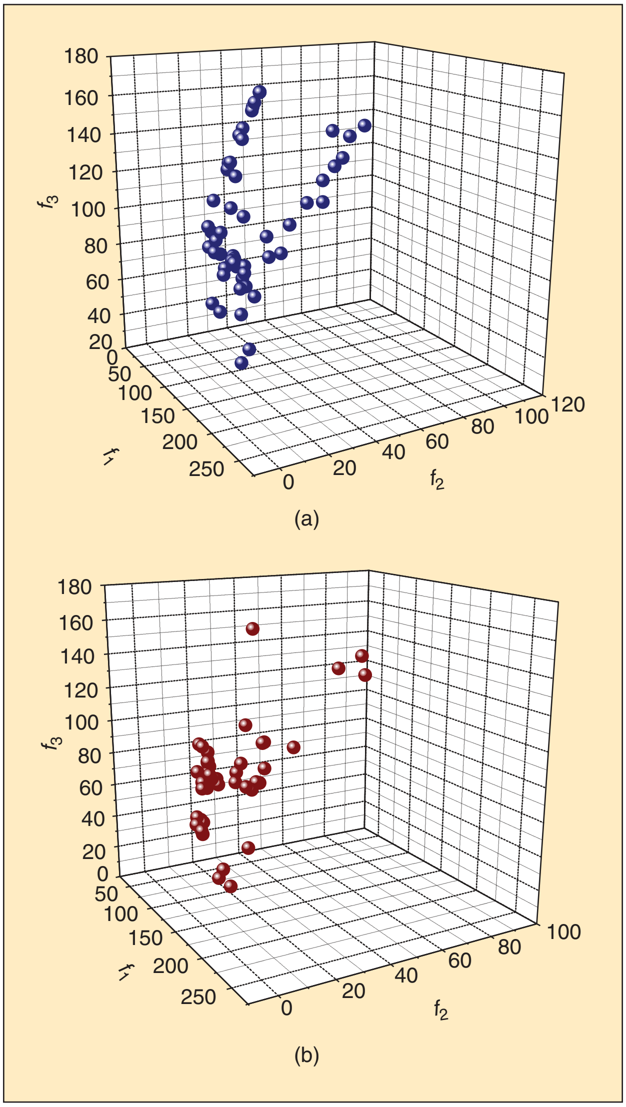

FIGURE 9 (a) Simulation results of nondominated solutions using NSGA-II and (b) Nondominated solutions using MOPBIL in a three-objective space.

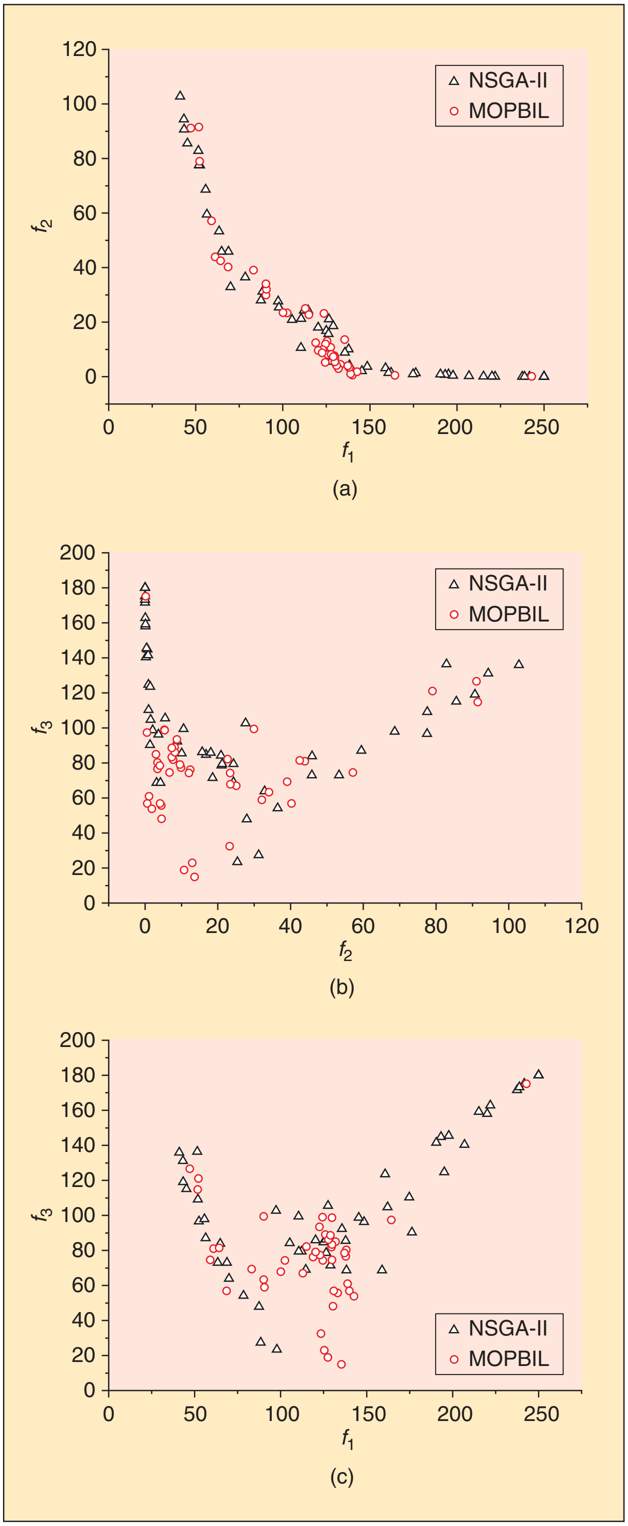

FIGURE 10 Simulation results of nondominated solutions of NSGA-II and MOPBIL in (a) $f_1 - f_2$, (b) $f_2 - f_3$, and (c) $f_1 - f_3$ objective spaces.

where P_i is the i^{th} element of probability vector, $0 \leq i \leq m$. m is the binary string length, LR is the learning rate, $0 \leq LR \leq 1$, and b_i is the i^{th} bit of the best binary solution. Mutation operator to the PV is as follows:

$$P_i^{\text{new}} = P_i^{\text{old}} \cdot (1 - ms) + \text{random}(0 \text{ or } 1) \cdot ms, \qquad (6)$$

where ms is the amount of mutation shift.

Conventional PBIL for MOP selects b_i using the mean of random solution in the archive or the random weighted sum. During the update of each probability vector, only one best individual b_i is referred to a reference solution. In the proposed MOPBIL, updating scheme of each individual is changed to refer randomly selected one among nondominated solutions in the archive as the best solution for enhanced performance. In other words, one of randomly selected nondominated solutions in the archive is referred when every update of each element of PV is carried out.

The overall architecture of MOPBIL for fuzzy path planner is depicted in Figure 7. MOPBIL algorithm runs around the loop until the termination condition. When the solutions are evaluated, the chromosome of each solution representing a fuzzy rule set is implanted to fuzzy navigation system. Vision system provides the fuzzy inference system with the relative posture information of robot to the ball. The fuzzy inference system calculates the desired heading angle, θ_d, of robot. Then, fuzzy path follower controls the robot to follow θ_d by calculating left and right wheel velocities, V_L and V_R. MOPBIL algorithm calculates the objective function values at the moment of kicking the ball or at the last moment of time limit, and evaluates the performance of the fuzzy path planner through this process.

4. Experiments

The performance of proposed MOPBIL was compared to that of NSGA-II for the optimization of fuzzy path planner by measuring performance metrics such as size of the dominated space ($\mathcal{S}$), coverage of two nondominated sets ($\mathcal{C}$) [34] and diversity metric ($\mathcal{D}$) [35]. Since NSGA-II is the most representative algorithm among the multiobjective evolutionary algorithms, it was chosen to compare with MOPBIL.

4.1. Simulation and Experiment Environment

Mandani's min-max inference for fuzzy reasoning [32] and weighted average method for defuzzification were employed in the fuzzy path planner. Simulation program was used for parameter optimization and algorithm verification. The simulated robot was assumed that it did not slip and had a limit in acceleration speed. Real number was encoded and Gaussian mutation was used as mutation operator for NSGA-II. Parameters used in simulations are given in Table 2, where the learning rate (LR) is to adjust convergence speed and ms is the amount of shift used in the mutation. 143 training points in total were used as shown in Figure 8. Heading angle at the training points and the initial rule set were randomly generated. Fitness value of each chromosome was the

TABLE 3 Comparing the coverage of two sets, the size of dominated space, diversity, and the simulation time.

ALGORITHMS	COVERAGE OF TWO SETS ($\mathcal{C}$)	SIZE OF DOMINATED SPACE ($\mathcal{S}$)	DIVERSITY	SIMULATION TIME
NSGA-II(A)	$\mathcal{C}(A, B)$= 0.181818	$5.142433897 \cdot 10^7$	**0.2534**	**17 min 50 s**
MOPBIL(B)	$\mathcal{C}(B, A)$= **0.410714**	$\mathbf{5.150735638 \cdot 10^7}$	0.0422	22 min 52 s

average value of evaluations at all training points. The comparison results were averaged over 10 runs. All the simulations was executed on a 2.8-GHz Pentium-IV PC with 2-GB RAM.

In experiments, the micro-robot soccer system was employed as a test bed, where a Pentium 4 IBM PC was used as a host computer, Uniqvision UC-685 10-bit color digital CCD camera was used as the vision camera and soccer robot had a DSP TMS320F2811 PBK as the micro-controller and two DC motors.

4.2. Simulation Results

Figure 9 compares the nondominated solutions in a three-objective space found by using the MOPBIL and NSGA-II. Figure 10 compares the nondominated solutions in three two-objective spaces, found by using the MOPBIL and NSGA-II for better display. Figures 10(a) and 10(c) show the similar performances in f_1–f_2 and f_1–f_3 objective spaces, respectively. However, Figure 10(b) shows that the nondominated solutions of MOPBIL were more minimized with respect to f_2 and f_3.

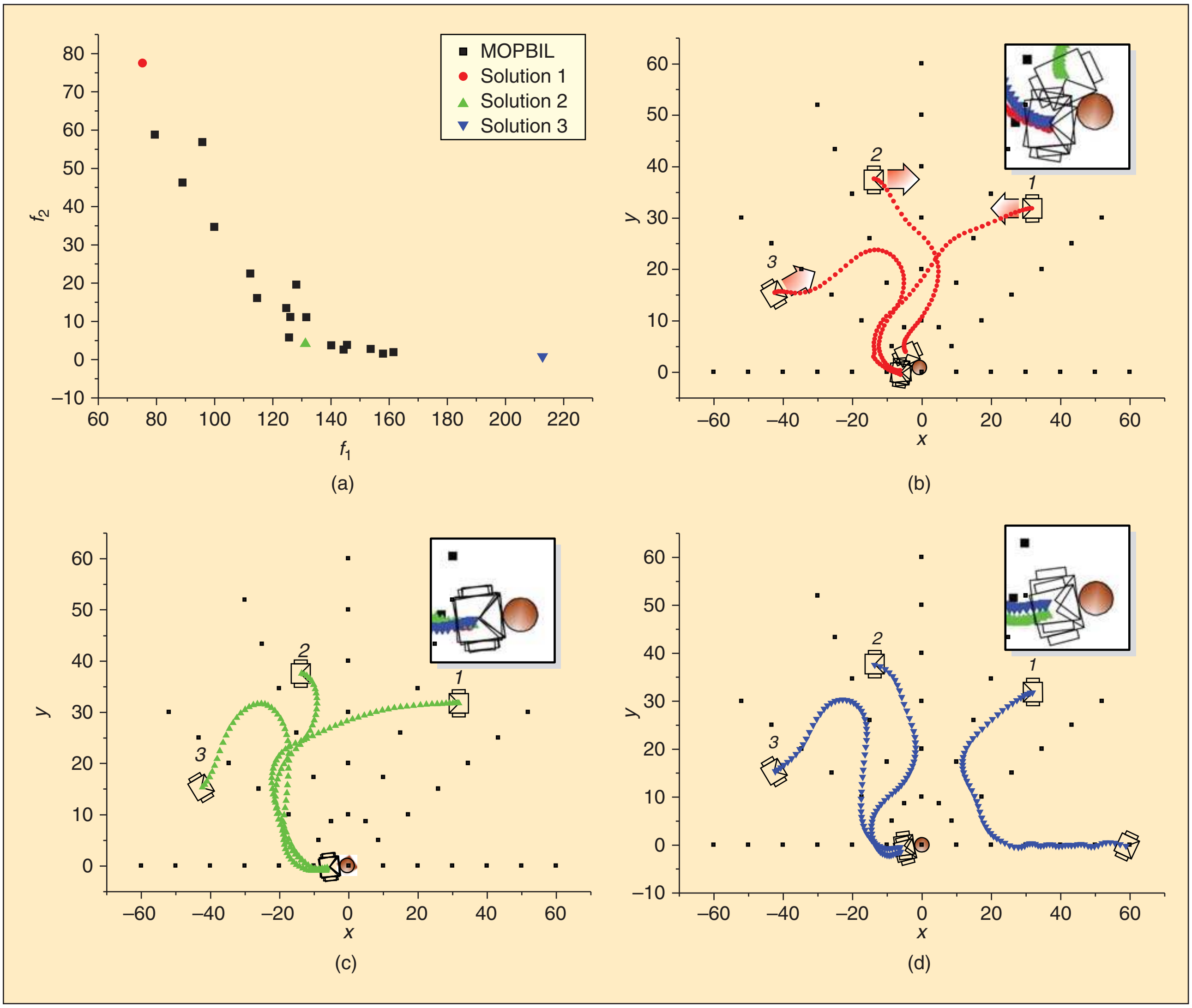

FIGURE 11 Simulation results of nondominated solutions obtained from MOPBIL for $f_1 - f_2$ objective space. (a) Various solutions of MOPBIL. (b) Simulation results when Solution 1 was used. (c) Simulation results when Solution 2 was used. (d) Simulation results when Solution 3 was used.

TABLE 4 Extreme solutions according to each objective.		
EXTREME VALUES	**SYMPTOMS**	**VIOLATED CONDITIONS**
MAXIMUM f_1	ROBOT DOES NOT APPROACH THE BALL (NO KICK).	ROBOT SHOULD KICK THE BALL.
MAXIMUM f_2	ROBOT KICKS THE BALL TO THE OPPOSITE SIDE (OWN GOAL).	ROBOT SHOULD KICK THE BALL TO THE RIGHT.
MAXIMUM f_3	ROBOT DOES NOT KICK OR KICKS TOWARDS OWN GOAL.	BOTH.

Table 3 shows the coverage of two sets, the size of the dominated space (hypervolume), diversity and the simulation time of MOPBIL and NSGA-II. The larger coverage value of MOPBIL represents that most of solutions of NSGA-II in each objective were dominated by those of MOPBIL. It means that MOPBIL could find higher quality solutions compared to NSGA-II. The rule set of MOPBIL could make the robot approach the ball faster and kick it more accurately. It was due to the probabilistic characteristics of MOPBIL, which resulted from a good balance between exploration and exploitation and the capability to select nondominated solutions when PVs get updated. Reference point that calculates the size of the dominated space was set to (400, 400, 400). The size of the dominated space of MOPBIL was larger than that of NSGA-II because the obtained solutions of MOPBIL dominated more in search space than those of NSGA-II. The results of diversity measure showed that NSGA-II performed better than MOPBIL on the distribution of solutions. Since NSGA-II was encoded by real number, the simulation time of NSGA-II was faster than that of MOPBIL encoded by binary representation.

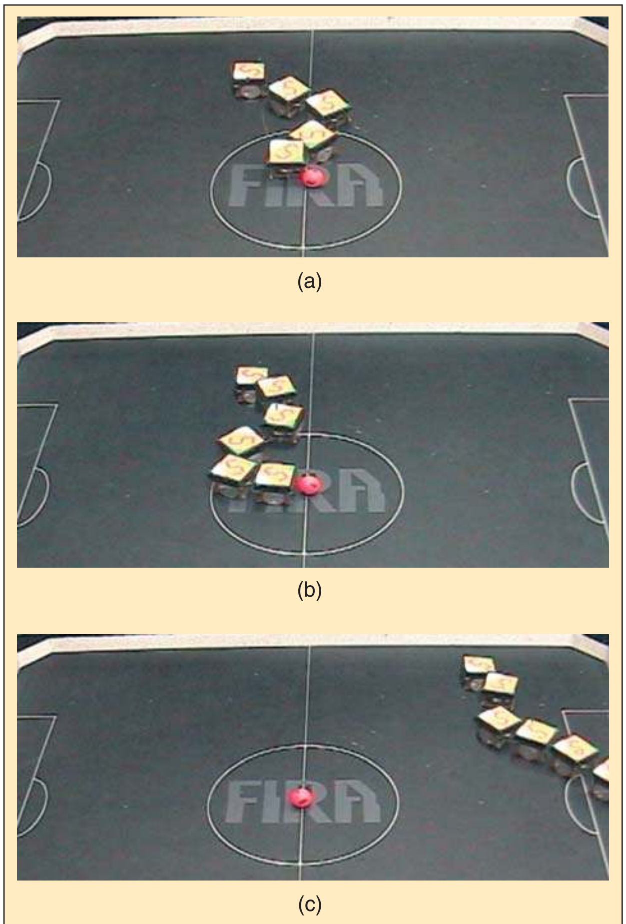

FIGURE 12 Experiment results of nondominated solutions obtained from MOPBIL for $f_1 - f_2$ objective space. (a) Using Solution 1 from the second inital testing position. (b) Using Solution 2 from the second initial testing position. (c) Using Solution 3 from the third initial testing position.

Figure 11 compares the trajectory of nondominated solutions obtained by MOPBIL. Figure 11(a) shows the obtained solutions when the proposed MOPBIL was applied and the rest of figures respectively depict the three initial testing positions and their corresponding trajectory by each of obtained solutions. When more optimized solution to f_1 (Solution 1) was applied to the robot, it showed faster approach to the ball (Figure 11(b)). On the other hand, when more optimized solution to f_2 (Solution 2) was applied, it kicked the ball more accurately (Figure 11(c)). Table 4 shows three extreme solutions, which could not satisfy these two necessary conditions. For instance, the robot using 'Solution 3' from the first initial testing position could not approach the ball (Figure 11(d)). Even though solutions from simulation were theoretically meaningful for MOP, they were not practically useful as a real path planner. It means the studies on decision making for a solution among the nondominated solutions could be a further research issue in real-world problems.

4.3. Experimental Results

Physical experiment was configured similarly as in simulation environment, where the ball was fixed at the center of playground and the starting points of robot were the same as the three initial testing points in Figure 11(b). Figure 12 shows the experimental results of nondominated solutions obtained from MOPBIL. Figures 12(a) and (b) compare the trajectories of the two obtained solutions from MOPBIL, when robot started from the second initial testing position. The robot in Figure 12(a) approached the ball more quickly, but it was not able to kick the ball exactly towards the goal. On the other hand, the robot in Figure 12(b) spent more time to approach the ball, but it kicked the ball correctly. The robot in Figure 12(c) started from the third initial testing position and it was not able to approach the ball as in the simulation result.

Consequently, it should be noted that user has to select an appropriate path planner for soccer robot according to the game situation or robot's role. For example, defender robot should possess a fast path planner (Solution 1) for active defending, whereas offensive robot should have an accurate path planner (Solution 2) for precise shooting. In any case, user should not select solutions like 'Solution 3' for the path planner because the elapsed time (f_1) is too long and moreover the robot cannot kick the ball within time constraint. Thus, user must decide the solution that lies within the boundary of time and accuracy constraints.

By applying various nondominated solutions from the MOPBIL to the soccer robot and evaluating the generated trajectory by each of them, the concept and mechanism of the computational intelligence-based navigation can be educated along with multi-objective optimization.

5. Conclusions

In this paper, robot soccer system was shown to be an effective and efficient educational platform for the education of computational intelligence-based navigation. As a navigation method for soccer robot an evolutionary fuzzy path planner was designed from the viewpoint of multi-objective optimization. To find out a desirable fuzzy rule set of the fuzzy path planner satisfying multiple objectives, multi-objective population-based incremental learning (MOPBIL) algorithm was proposed. It was demonstrated that solutions from MOPBIL were closer to Pareto optimal front than those from NSGA-II. In real experiments, the proposed MOPBIL algorithm efficiently provided better solutions with respect to the multi-objectives of the path planner. By applying various nondominated solutions from the MOPBIL to the soccer robot and evaluating the generated trajectory by each of them, the concept and mechanism of the computational intelligence-based navigation can be educated along with multi-objective optimization. Through the education, more innovative strategies in robot soccer can be created and better understanding of intelligent system is expected.

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