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RFID Sensor Deployment using Differential Evolution for Indoor Mobile Robot Localization

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Abstract— **This paper presents the sensor deployment method to design a RFID sensor network for the mobile robot localization using evolutionary approach. For this purpose, we employ the differential evolution (DE), which is well-known for promising performance. We propose two variation methods, the direct optimization strategy for the maximum usage of initial information intuitively and the full coverage optimization strategy for the dense coverage for the surveillance and the security. In that case, the proper tuning of parameters of DE is essential. We experiment sensor deployment in two maps for providing guidance about parameter tuning. The experimental results show better sensor deployment result according to guided parameter setting. The full coverage optimization strategy also shows proper result using guided parameters from the standard DE case.**

I. Introduction

The mobile robot localization using RFID sensors in indoor environment has been researched recently. [1] Most localization method is that RFID tags are attached or installed in the floor and RFID antenna is attached on the mobile robot. However, for the localization of multiple mobile robots, RFID tags are attached on the robot, instead antenna and RFID antennas are installed in the environment [2]-[4]. In this paper, the optimal RFID sensor deployment problem is appeared.

Most common sensor deployment way is to place sensors manually by means of expert's intuition or experience. Experts arrange sensors coarsely in interest area considering coverage and interference among sensors, and then rearrange sensors by trial and errors. Another approach is a mathematical way. The exact deployment solution is also calculated in a simple environment using a minimum sum of radii cover [5] or a polynomial time approximation scheme [6]. The last method is to define a sensor deployment problem as a meta-heuristic search problem. The sensor deployment is formulated as a search problem to minimize the number of turning on sensors as well as to maximize the total coverage of sensors as in the mathematical approach. For this purpose, various search algorithms, such as tabu search, generic search [7], [8], simulated annealing [9], [10], swarm based algorithm [11], and so on, are applied to sensor deployment problems.

However, above researches are not less related with sensor deployment for indoor mobile robot localization, since there are no specific consideration for reducing computational cost and time. In this paper, we propose optimal sensor deployment in complex indoor environment using differential evolution(DE). In addition, in order to get reasonable solutions with initial set similar with expert's trial and direct evolution, we also proposed the direct optimization strategy with DE. The parameter study of DE with new strategy also is considered, due to optimization performance dependency on control parameters of DE. For the strict mobile robot localization, full coverage optimization strategy is also proposed since there are little dead zone by sensors in the perspective of surveillance and security.

The reminder of this paper is organized as follows. We introduce main components of the optimal sensor deployment problem with DE in Section II. Overview, detail and procedure of proposed sensor deployment using the DE, the direct optimization strategy and the full coverage optimization strategy are introduced in III. Section IV shows experimental results that our proposed sensor deployment solutions are reasonable by composing network system with RFID antennas and tags before we conclude the paper in Section V.

II. Sensor Deployment With Differential Evolution

In this section, optimal sensor deployment problem is briefly described.

A. Indoor environment

Indoor Environment can be divided into 2 regions. One is an user interest region. Many places including rooms, corridors and halls can be selected as a user interest region according to aims of each mobile robot system. All UIR should be covered by minimum number of sensors attached from the ceiling or wall, outside the robot.

Other is an obstacle region. If some obstacles are placed in specific region, then a mobile robot can't be located that position. In other word, the unreachable place for a robot is not required to cover by sensors. In fact, the coverage of that place of sensors cannot be meaningful to user. Thus in order to use minimum number of sensors as much as possible, the effort spent on covering obstacle region of sensors should be decreased.

B. Sensor representation

To solve sensor deployment problem, the common property of a sensor is represented by control variables. Needless to say, there exist distinct features for sensor types. Thus, common features, the sensor's position, detection range and

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on/off state are only used to represent information of sensors in this paper.

The position of ith sensor is represented as x_{i_1}, x_{i_2}, a point located in the xy-plane. In other words, it assumes that the height of all sensor location is fixed or the detection range of each sensor is adjusted for the height of sensors, respectively.

The detection range level of sensor is represented as x_{i_3}. In the xy-plane, the detection range is defined as a radius of a disk centered on the position of ith sensor x_{i_1}, x_{i_2}. It assumes that user can adjust the detection range of each sensor.

The 'on/off' state of a sensor is represented as x_{i_4}. The 'on' state of a sensor means that sensor will be installed according to the position and the detection range level, whereas the 'off' state means that sensor will be eliminated. For the use of minimal number of sensors, sensors with the 'off' state should be increased in the map. Finally, ith sensor among $i = 1, 2, ..., M_s$, where M_s is a maximum number of sensor from geometric solution, is represented as $x_i = \{x_{i_1}, x_{i_2}, x_{i_3}, x_{i_4}\}$.

C. Differential Evolution

DE is a stochastic search algorithm that is originally motivated by the mechanisms of natural selection. The DE is a population-based stochastic function optimizer that is very effective for solving optimization problems with non-smooth objective functions. Also simple yet powerful and straightforward features make DE very attractive for optimization. Compared as other EAs, DE uses a rather greedy and less stochastic approach to problem solving. In order to get a final solution, DE combines simple arithmetical operators with the classical operators of recombination, mutation, and selection to evolve from these randomly chosen initial points [13], [14].

In this experiment, the $DE/rand/1/bin$ is used as a standard DE. *rand* indicates the method for selecting the parent chromosome randomly, 1 indicates the number of difference vectors used to perturb the base chromosome, *bin* indicates the binary recombination mechanism to create the offspring population.

III. Proposed RFID Sensor Deployment Strategy With Differential Evolution

In this section, the organization and procedure of sensor deployment algorithm using DE are presented. In order to apply DE in sensor deployment problem, it is essential for defining and organizing fitness assignment, perturbation operators, initialization process, and parameter settings of DE. These topics are presented as following subsection. In addition, not only the DE itself, but also additional optimization strategies with DE are also described.

A. Aggregation of fitness functions

Three objectives are considered in this optimal sensor deployment problem.

1) Coverage Rate: The coverage rate is the portion between the region covered by all sensors with 'on' state and whole user interest regions. The coverage rate, R_c, is calculated as follows.

$$R_c = N_c/(N_c + N_u)\% \tag{1}$$

, where N_c is the interest region covered by sensors and N_u is unavailable region covered by sensors. When whole user interest region is covered by all sensors with 'on' state, coverage rate indicates 100%.

2) Interference Rate: The interference rate is the portion between the overlapped regions by two or more sensors. The interference rate, R_i, is calculated as follows.

$$R_i = N_i/(N_i + N_u)\% \tag{2}$$

, where N_i is the overlapped region except the obstacle region. The interference rate means the waste of effort of each sensor. High interference rate can be reduced by decreasing the number of sensors.

3) Number of Sensors with 'on' State: The number of sensors with 'on' state, N_s. Previous objective functions are continuous function over 0 to 100, whereas this objective function is given by integer function. N_s affects directly cost composing overall system. The number of sensors is integer, thus the influence is stronger than the interference rate, but the freedom of degree is lower than the interference rate.

In the weighted sum approach, we use uncovered rate, which is defined as $f_1 = 100 - R_c$, rather than coverage rate itself. The interference rate is used directly, $f_2 = R_i$. The normalized number of sensors is represented as the portion of the number of sensors with 'on' state over geometrical solutions for the unconstraint condition, which is defined as $f_3 = N_s/M_s$. Thus the final form of fitness is $F = w_1 f_1 + w_2 f_2 + w_3 f_3$.

B. Additional optimization strategies with DE

In addition to the standard DE, additional optimization strategies are provided as follows. One is the direct optimization strategy for reduction of computational cost with initialization process and the direction of evolution of standard DE. The other is the full coverage optimization strategy for mobile robot localization.

1) Direct optimization strategy: The DE such as other evolutionary algorithms, which usually shows a good optimization performance, seem to be have a lot of computational cost and time to get solutions from scratch. If possible, to reduce cost and time without significant interference for mobile robot localization is useful. Considering computational cost and time, the selection of initial population can be an issue. In addition, to push the initial population toward optimal direction may lead to reduce computational cost and time, the direction of evolution seems to be important required. The DE also has parameters for controlling the degree of evolution and the trade-off between exploration and exploitation. For the mobile robot localization, the direct optimization strategy is proposed as follows.

First of all, the R_c, one of the objective functions, is considered for evolution with the strong effect of the population of initial and early stage. The purposes of the first stage are to decrease the computational steps. The other purpose is to decrease the computational cost by neglecting the R_i . The R_c is calculated easily by the difference of all user interest region, thus no matter how much sensors are located in a map, and one calculation is enough to find the R_c. However, the R_i is calculated by overlapped region which should be considered not only uncovered region, but also the region that is covered by sensor just once, so more computational cost and time is required. When an individual with above 90% R_c appears, the first stage is finished and the second stage starts.

In the second stage, a DE tries to reduce R_i which doesn't optimize at all in the first stage. The system not allowing switching 'off' state into 'on' state of sensors during the second stage, the number of sensors with 'on' switch can be decrease but not increase. Changing detection range and moving the position of sensors, the system reduces the R_i . When R_i reaches 20%, the last stage is operated.

The last stage is free optimizing stage without any more constraint over the standard DE. During previous two stages, the system tries to find the individuals and compose the population as reasonable solution candidates.

2) Full coverage optimization strategy: The cost-effective sensor deployment seems to be important for composing sensor networks. However, considering the purpose of surveillance or security, full coverage by sensor becomes most important priority of all. This strategy is different from previously mentioned strategies, in the perspective of full coverage by sensors. In order to minimize the cost composing sensor network, the N_s should be reduced. It must lead to lose coverage in user interest region. This strategy emphasizes the whole user interest region should be covered by sensors regardless of cost and the N_s, whereas the previous strategies lead to compose cost-effective sensor network. In the whole evolution process, if the R_c is below 99% then, a lot of penalty is given to each individual. Therefore only full coverage individuals survive for a long time among population. The R_i and the N_s are relatively neglected compared as the R_c. This may lead to deploy more sensors in the map, thus increasing the overall cost composing sensor networks. However, there is little dead zone in the user interest region to cover by sensors, then the mobile robot localization performance for surveillance and security is better than the standard DE and the direct optimization strategy.

C. The framework of the proposed sensor deployment system

* indicates the direct optimization strategy

** indicates the full coverage optimization strategy

Step 1) Initialization of an individual population

Initialize a population of individuals with random values generated according to a uniform probability distribution in the dimensional problem space.

* Initialize sensors with random position, but maximum detection range and 'on' state.

Step 2) Evaluation of the individual population

Evaluate the fitness value of each individual.

* 1st stage : Only R_c is considered.

* 2nd, 3rd stage : Weight sum approach is used.

** Below 99% R_c, the penalty is imposed. Only the R_i and N_s are considered.

Step 3) Mutation operation

Adds a vector differential to a population vector of individuals according to the following equation:

$$z_i(t+1) = x_{i,r1}(t) + F[x_{i,r2}(t) - x_{i,r3}(t)] \quad (3)$$

where $i = 1,2,...,M_s$ is the individual's index of population, $j = 1,2,3,4$, is the X,Y position, the detection range and on/off state of each sensor, respectively. The t is the generation. The r_1, r_2 and r_3 are randomly selected with uniform distribution from the set $\{1,2,...,i\text{-}1,i\text{+}1,...,M_s\}$.

* 1st stage : Mutant vector is generated with a random position, maximum detection range and 'on' state.

* 2nd stage : Mutant vector is generated with a random position, random detection range. State transition into 'on' is not allowed.

* 3rd stage : same as a standard DE.

Step 4) Recombination operation

Recombination generates a trial vector by replacing parameters of the target vector with the corresponding parameters of a randomly generated donor vector. For each vector, $z_i(t+1)$, an index $rnbr(i) \in 1,2,...,n$ is randomly chosen using uniform distribution, and a trial vector, $u_i(t+1) = [u_{i_1}(t+1), u_{i_2}(t+1), u_{i_3}(t+1), u_{i_4}(t+1)]^T$, is generated with

$$u_{i_j}(t+1) = \begin{cases} z_{i_j}(t+1), & \text{if}(randb(j) <= CR) \\ & \text{or}(j = rnbr(i)) \\ x_{i_j}(t), & \text{otherwise} \end{cases} \quad (4)$$

Step 5) Selection operation

Selection is the procedure of producing better offspring. If denotes the objective function under minimization, then

$$x_i(t+1) = \begin{cases} u_i(t+1), & \text{if} f(u(t+1)) < f(x_q i(t)) \\ x_i(t), & \text{otherwise} \end{cases} \quad (5)$$

Step 6) Verification of stop criterion

Set the generation number for $t = t+1$. Proceed to Step 8 until a maximum generation G_{max} is met.

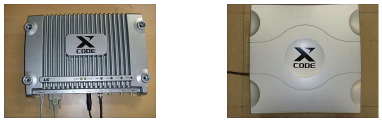
Step 7) Stage change criterion

1st stage to 2nd stage : above 90% R_c

2nd stage to 3rd stage : below 20% R_i

IV. Experimental Results

In this section, our sensor deployment performance is verified by experiments. We carry out the sensor deployment with the RFID antenna/tags. RFID system is widely used to check tagged products in a wide area. Commonly, a RFID reader is too expensive to install to cover a wide area. Therefore, a measurement data of RFID antenna empirically obtained from experiments and apply to deployment of a



(a) (b)

Fig. 1. Commercial RFID sensors utilized in this paper. (a) IU 9003 readers (LS Electronics) (b) UHF RFID antennas (LS Electronics)

multiple RFID antennas. The target robot of this experiment is the entertainment mobile robot. The mobile robot is used to check whether the location information of the mobile robot is transferred via RFID antennas to RFID reader in user interest region.

A. Experimental conditions

IU9003 (LS Electronics) is utilized as RFID reader and antennas in this paper. Operating frequencies of IU9003 is respectively from 910MHz to 914MHz with a circular polarization type. Antennas are installed on the ceiling, 2.5m above the floor. 180074-001 is used as passive-type RFID tags. Fig. 1 shows the equipment which provides sensing data.

The RFID sensor deployment has been tested using entertainment mobile robot equipped with the 2-axis differential wheel. This robot already has a sonar sensor and a vision sensor for navigation and object tracking, however, for composing system for multiple mobile robot localization, built-in sensors of robot are not used in this experiment. Fig. 2 shows the mobile robot used in this experiment.

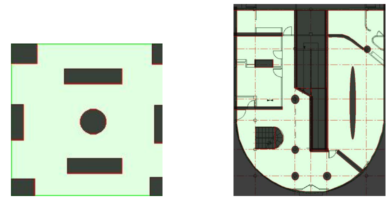
Fig. 2. The target entertainment mobile robot in the experiments

The experiments use two user maps: a hall and a corridor. The maximum number of antenna M_s are 13 and 18 in the Hall and Corridor, respectively. Fig. 3 shows the Hall and Corridor type maps. The corridor type map is extracted by CAD and the hall type map is extracted by user's arbitrary drawing map.

Deployment algorithms with a standard DE, the direct optimization strategy and the full coverage optimization strategy, three methods are used to experiment. To verify different usage of parameters of DE, 9 pairs of difference amplification factor and crossover rate is used in a standard DE and direct optimization strategy. Full coverage optimization strategy uses the best parameters from the experiment of a standard DE case.

The specific parameter setting of a DE is as follows.

- Population size, N_p =50



(a) (b)

Fig. 3. Maps for sensor deployment (a) the hall type map (b) The corridor type map

- Maximum number of generations, $G_{max} = 20 * M_s$
- Crossover rate, CR = 0.2, 0.5, 0.8
- Difference amplification factor, F = 0.2, 0.5, 0.8
- Second stage entrance condition, f_1 = 90%
- Third stage entrance condition, f_2 = 20%
- w_1, w_2, w_3 = 0.735, 0.245, 0.02

Generally R_c is most required objectives in sensor deployment problem, thus determining 3 times of priority compared with that of R_i . As previously mentioned, because N_s is not continuous objective function, it can disturb optimization in the weight sum approaches. By adjusting w_3 is smaller by 0.1 degree, N_s can affect the optimization result in later generation, When R_c and R_i are small enough.

The experiments are performed on a computer with Intel Core2Duo E4500 2.20GHz and 3.25GB of RAM in Visual c++ 2008 under the Microsoft Windows XP SP3.

B. Parameter study of the standard DE and the direct optimization strategy

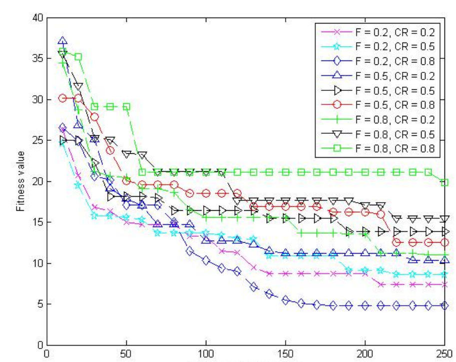


Fig. 4. Fitness convergence property: The hall type map with the direct optimization strategy

The Figures from Fig. 4 to Fig. 7 show the fitness convergence property versus control parameters of the standard DE and the direct optimization strategy in the hall and corridor type map respectively. First of all, Fig. 4 shows fitness converge property of optimization with a standard DE in a Hall type map. The best performance comes out in CR=0.8, F=0.2. This parameter set means higher CR and lower F value are proper for the standard DE. Second and third rank has same F value as the first rank and CR value are 0.2 and

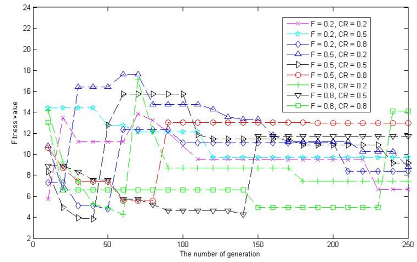


Fig. 5. Fitness convergence property: The hall type map with the direct optimization strategy

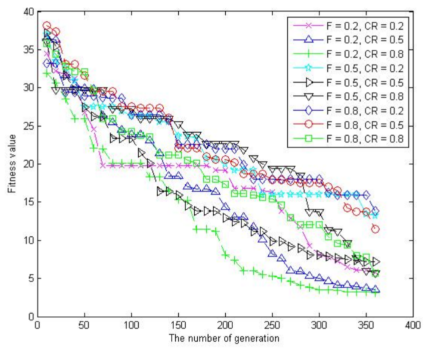


Fig. 6. Fitness convergence property: The corridor type map with the standard DE

0.5 respectively. As F value gets higher, performance gets worse. When F value gets higher, in other words, difference amplification affects much to generate mutant vector, thus exploration is maximized. When CR value gets higher, a lot of recombination chance is appeared. In a standard DE with random initialization case, the mutant vector generated from difference of vectors of current individual is helpful to search global optimum. However, a mutant vector with a large variation due to large F may lead to random search, because the mutant vector changes too much from individuals of previous generation. In summary, higher CR, which leads to reflect the mutation vector much in evolution, helps to find optimal solution, whereas higher F, which leads to change the mutation vector from past information too much, interfere the effect of selection for finding global optimum. Fig. 6 also shows the best optimization result with higher CR and lower F. In the Fig. 5 and Fig. 7, the fitness convergence property of direct optimization strategy is shown. There are fitness jump which is different property compared as the standard DE, is due to change from first stage to second stage. As previously mentioned, only the R_c is considered as fitness function in first stage, and if the R_c is above 90%, then enter the second stage which fitness comes back to the weighted sum of the R_c, R_i and N_s. Thus, when stage changes, fitness jump phenomenon is appeared. It seems that F=0.8, CR=0.2 shows good optimization performance, in fact, it is failed to find 90% R_c solution, and then it is impossible to enter the second stage. Large F interfere the convergence by similar reason with the standard DE. Other noticeable result is the result of CR=0.8, F=0.2. This parameter leads to worse result compared as the standard DE. Because the initialization of the direct optimization strategy makes the initial population gather near local optimum by turning on all sensors with maximum detection range. Thus, small variation of current solution is helpful, otherwise mutant vector follows current population vector too fast. In other words, the diversity loss is too fast with higher CR. In summary, lower CR, which leads to small step size with careful search near the local optimum, which is similar with expert's trial and error intuitively and lower F, which leads to the mutation vector related with the current population vector is helpful for finding global optimum.

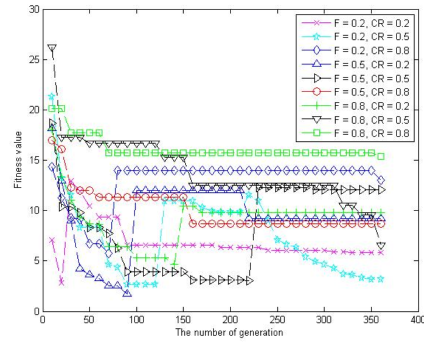
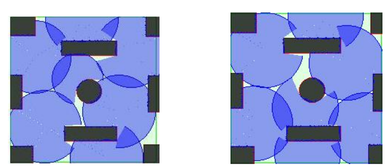
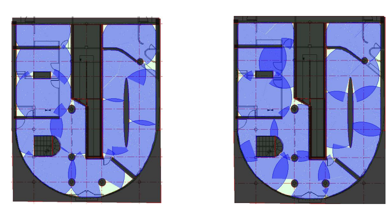


Fig. 7. Fitness convergence property: The corridor type with the direct optimization strategy



(a) (b)

Fig. 8. Best sensor deployment solution for the hall type map (a) with the standard DE (b) with the direct optimization strategy

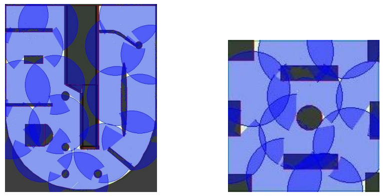


(a) (b)

Fig. 9. Best sensor deployment solution for the corridor type map (a) with the standard DE (b) with the direct optimization strategy

C. Best optimization results

1) The standard DE and the direct optimization strategy: Fig. 8 and Fig. 9 illustrate the optimization results of sensor deployment with the standard DE and the direct optimization



(a) (b)

Fig. 10. Best sensor deployment solution with the full cover strategy (a) for the corridor type map (b) for the hall type map

strategy in the hall and corridor type map, respectively. The blue circles represent the detection range of each sensor in last generation. The center of circle is the location of installed sensor. The black regions represent the obstacle regions and the green regions represent uncovered regions among user interest region. The dark blue regions represent the interference regions among two or more antennas. The R_c is 96.3%, the R_i is 8.56%, and N_s is 7, whereas the R_c is 95.6%, the R_i is 7.05%, and the N_s is 12 with the standard DE and the direct optimization strategy respectively in the corridor type map. The R_c is 93.1%, the R_i is 7.34%, and the R_s is 13, whereas the R_c is 95.8%, the R_i is 5.26%, and R_s is 12 with a standard DE with the standard DE and the direct optimization strategy respectively in the corridor type map. In fact, it seems to be no difference between the standard DE and the direct optimization strategy. In the best parameter setting of the standard DE and direct optimization strategy respectively, both algorithm shows high-quality optimization results.

2) Full coverage optimization strategy: Fig. 10 illustrates the deployment result of sensors with the full coverage optimization strategy in the hall and corridor type map. The results show that more antennas are placed for covering the whole user interest region densely compared as those of the standard DE and the direct optimization strategy. The R_c is 99.0%, the R_i is 27.3% and the N_s is 16 in the corridor map with the full coverage optimization strategy. Meanwhile, the R_c is 99.2%, the R_i is 29.4% and the N_s is 10 in the hall map with the same strategy. The results of both case show the dense R_c in the mobile robot localization for surveillance and security, whereas the N_s is increased by 30%. Since increment of the N_s directly lead to expensive cost to compose sensor networks. In perspective of cost, above results in each map can not be survived in the standard DE and direct optimization strategy. However, if the priority of overall R_c is important regardless of cost, then the full coverage optimization method is more proper than previous strategies.

V. CONCLUSION

This paper presents the sensor deployment method to cost-effectively design a RFID sensor network for the mobile robot localization. We employ the DE, which is well-known for promising performance, and propose direct optimization strategies for sensor deployment. We experiment sensor deployment in two maps for providing guidance about parameter tuning with a mobile robot. Using guided parameter setting in each algorithm, successful sensor deployment optimziation solutions are obtained in two type of maps, Corridor and Hall, with both algorithms in the case of the standard DE, direct opimization strategy and full coverage optimization strategy.

In our future works, we will extend to adopt this algorithm for path planning and indoor navigation of mobile robots as well as static sensor deployment.

VI. ACKNOWLEDGMENTS

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