

# A NEW GENETIC ALGORITHM WITH SELF-CONFIGURATION CHROMOSOME TO DISCOVER OPTIMAL FLEEING PATHS IN BLAZE SCENE

Mong-Fong Horng, Yi-Ting Chen, Sin-Man Zeng and Bing-Yi Liao  
Dept. of Electronic Engineering  
National Kaohsiung University of Applied Sciences  
email: [mfhorng@ieee.org](mailto:mfhorng@ieee.org)

## Abstract

In this paper, a new genetic algorithm with self-configuration chromosomes for optimization is proposed. In legacy approaches, the chromosomes are with a constant structure. Thus, the search driven by genetic algorithm in solution space is not efficient. In this paper, a scheme of configuring chromosome structure is presented. The chromosome structure is adjusted according to the solution space. The proposed scheme is composed of three phases; solution space analysis, chromosome configuration and genetic operation. Through three phases, the chromosome structure is derived from solution space analysis and is adjusted in iterations to approach the optimal solution. The proposed scheme is applied to find the shortest secure path for people in blaze scene. We deploy a wireless sensor network to collect the temperature distribution in a blaze scene. The proposed genetic algorithm will discover the fleeing path from the measured temperature distribution. The experimental results show that the proposed scheme features (1) effectiveness (2) timeliness and (3) reliability. The developed system also benefits the security and safety of people in business buildings.

**Keywords:** Genetic Algorithm, Self-configuration chromosome, Wireless Sensor Networks, Blaze Rescue, Optimization

## I. Introduction

Computation intelligence [1] is a developing methodology for solutions of NP-hard problems. Computational intelligence is also vital to enable or facilitate intelligent machines in varying environments. There are significant paradigms of computational intelligence proposed in the past decades, including neural networks[2, 3], fuzzy logic [4], ant colony [5], swarm intelligence [6], artificial immune system [7] and evolutionary computing [8-11]. Although these paradigms are characterized in computational resource requirement, flexibility and optimality, the past works have verified their feasibility in a diversity of engineering and scientific applications.

Genetic algorithm (GA) proposed by Holland [8] is one of the most popular evolutionary algorithms. In the past decades, GA had been successfully applied to optimization problems, artificial intelligence and machine learning. GA offers an analogy of evolutionary process to solve optimization problem in engineering. In this evolutionary process, the individuals of each generation are evaluated by their fitness. Based on the principle of

survival-of-the-fittest, few individuals are selected for recombination and mutation to reproduce better offspring.

Wireless sensor network (WSN) is composed of tiny-sized, low-power and self-configured sensor nodes. The identical sensor nodes communicate with each other in radio and are deployed in an ad hoc topology. The connections between nodes are established and managed in a distributed manner. The deployed nodes organize the routing path for data delivery by themselves. All sensed data is aggregated to a data sink node for applications. Thus, WSN benefits the monitoring of physical systems, environments with the features of real-time, long-life, accuracy and reliability. ZigBee and IEEE 802.15.4 are the major protocols of wireless sensor networks to regulate the operations in PHY/MAC/Network layers.

Fire rescue is a significant issue in worldwide. According to the annual report from International association of fire and rescue service (CTIF), in the past decade, there are 7~8 million fires occurring on earth annually. These fires cause about 70,000 fire death and approximately 800,000 fire injuries. The 90% of fire deaths occurs in dwelling and business buildings. Moreover, as the social economics growth, large, even huge, shopping malls are built for people shopping, leisure and entertainment. The public facilities usually have long and complicated paths on floors. Upon the occurring of fire alarm, the customers in the mall shall be leaded safely to the closest exit for rescue. However, in the fire scene, people likely are besieged by high-temperature areas, heavy smoke and obstacles. How to rescue the people in a fire scene and to guide them to escape from the fire scene is the critical topic to be explored in this paper. Traditionally, fire siren is a common way to warn people for escape. Particularly, in a fire scene, lighting and layout of environment are changed due to power failure and furniture burning. Only fire siren is not able to prompt people how and where to escape safely and effectively. Thus, in this work, we deploy a wireless sensor network to monitoring the temperature distribution in buildings. Through the real-time measurement of space temperature, fire could be detectable. In a fire scene, the measured temperature distribution will be analyzed to derive fleeing paths for people to escape. The derivation of fleeing paths is a heavy computation job. The proposed self-configured chromosome effectively adapts the search in the solution space. Finally, the optimal fleeing paths are obtained in short.

The rest of this paper is organized as follows. The related work with regards to genetic algorithm and wireless sensor networks is reviewed in Section2. In

Section 3, a fleeing path guide system in fire scene (FPG) is presented. The presented system is composed of a wireless sensor network to measure the temperature distribution and a new genetic algorithm with self-configured chromosome to derive optimal fleeing paths from temperature distribution. The performance of effectiveness and efficiency is verified in Section 4. Finally, we conclude this work in Section 5.

## II. Related Work

In existed buildings, the fire alarm and hydrant systems are composed of flame detectors, smoke detectors and sprinklers. The sprinkler is activated if the corresponding detector is activated. The detectors usually are binary; on and off. The mechanism is not flexible and not programmable. False alarm and late alarm are the common problems encountered in real applications. Addition to fire alarm, the rescue guidance is also important in the construction of fire alarm systems. The safe and reliable fleeing path guidance is neglect in the existed system.

ZigBee [15] is with high scalability, reliability, easy deployment, low-cost, low-power and long-life to support simple interface for sensors and effective data transmission. Due to wireless communication and low-cost, ZigBee nodes are easy to deploy in masses for measurement of physical signals such as temperature, humidity, luminance, gas and so on. All measurements are delivered in a hop-by-hop way toward to the specific data sink for further applications. In past, ZigBee has been successfully applied in agriculture [16] microclimate [17], surveillance [18, 19], and disaster relief [20]. These applications with the premium monitoring quality and performance prevent the damage of human and property. However, due to the real-time and large measurement, the process of large data set is a critical challenge for real-time applications. Consider the routing problem of seeking the fleeing path in an  $m \times n$  grid with no obstacle. From the left-up corner to the right-bottom corner, the number of the possible shortest path paths without loop,  $N$ , is given as

$$N(m, n) = \binom{m+n}{n} \quad (1)$$

And the possible longest path will have the length of  $(mn-1)$ . Obviously, the search of optimal solution is with high computation complexity. The approach based on exhausted search can not fit the requirement of real-time application. Thus, a genetic algorithm is developed for this application. GA was proposed by Holland [8] according to the principle of survival-of-the-fittest. From the initial generation, offspring is reproduced by the crossover and mutation operations from parents. All offspring are evaluated by a defined fitness function. The offspring with better fitness are selected for the next generation, the others are discarded. The offspring is coded with strings. Each string represents a chromosome of offspring. Each chromosome is a possible solution of the fitness function. Through the process of selection, reproduce and fitness evaluation guided by the fitness function, an optimal solution is approached in the huge solution space. In the past work, there are lots of

researches working on the optimization of genetic algorithm. They expects a more efficient and reliable genetic algorithm. Bingul [10] proposed a genetic algorithm to solve dynamic multiobjective problems. Neikum *et. al.* [21] present presents a genetic programming algorithm to search for alternate reward functions that improve agent learning performance. Srinivasa *et. al.* [22] propose a self-adaptive migration model GA (SAMGA), where parameters of population size, the number of points of crossover and mutation rate for each population are adaptively fixed. However, the solution space for searching is neither simplified nor reduced.

The proposed self-configured chromosome (SCC) with adaptive chromosome length is applied for the search of optimal solution with more efficient search strategy. Before the construction of chromosomes, the chromosome length is derived from the analysis of optimal solutions. The evolution of optimal solution will be started from the shortest chromosomes due to the shortest-path-first strategy. Such a strategy is also effective for the reduction of search time and for real-time fleeing path prompt. The proposed SCC is able to find fleeing paths in various path lengths for more reliable rescue assistance.

## III. Fleeing Path Guide System in Blaze Scene

### III.1 Application Scenario

The application scenario is shown in Fig. 1. In the scenario, there are two major parts; detection modules and a guide module.

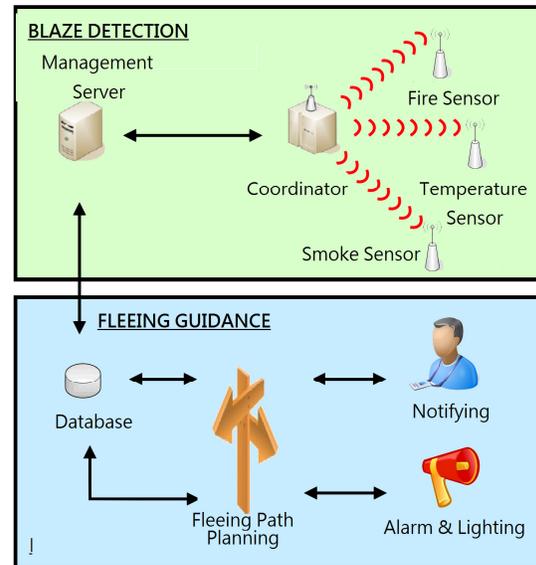


Fig. 1 Application scenario of Fleeing Path Guide System.

Detection module is a ZigBee network connecting flame detectors, smoke this detectors and temperature detector. In paper, the temperature detector is used to measure the local temperature of each node and forward the guide module receives the temperature measurement from detection modules, derive available fleeing paths, and notify the nodes on fleeing paths to turn on their lights for

indication. The major functions of FPG system are (1) The received environmental data could be logged in remote data servers. That is helpful for the fire investigation in future. (2) The blaze detection is not only by flame also but by the temperature distribution; (3) The guide system employs LED lighting and pre-recorded audio to prompt the available fleeing path; (4) The real-time and continuous monitoring and derivation of fleeing paths are in response to the dynamics of fire scene.

The guide module derives the fleeing paths by the proposed approach with the measurement of temperature distribution. First, consider a fire scene modeled as  $n \times n$  grid, a  $5 \times 5$  example is shown in Fig. 2,

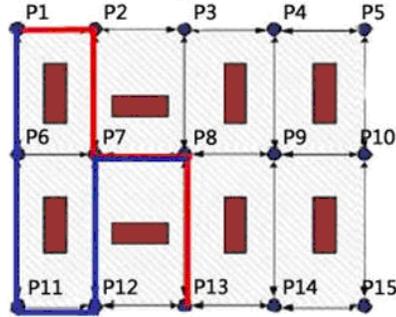


Fig. 2 The layout and coordinates of a floor in buildings. The representation of a fleeing path represented by a chromosome coding as

$$C(l) = (d_1, d_2, d_3, \dots, d_i, \dots, d_l) \text{ for } d_i = 0, 1, 2, 3 \quad (2)$$

where  $l$  is the path length and  $d_i$  stands for the selected direction next step; including right, down, left, up. A chromosome composed of  $l$  directions represents a fleeing path. For an example as shown in Fig. 2, the red path is represented as  $C_{red} = (0, 1, 0, 1)$  and  $C_{blue} = (0, 0, 1, 3)$  depicts the blue path.

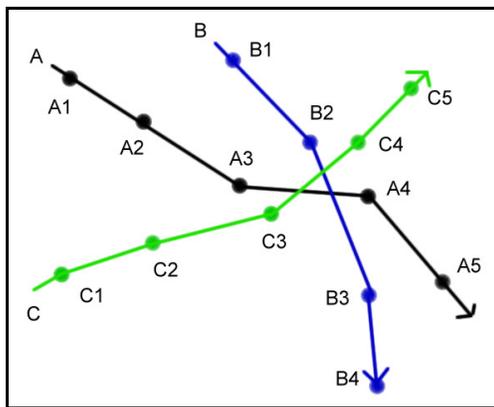


Fig. 3 Examples of fleeing paths

Certainly, in a blaze scene, there likely are various exits for people in various location to flee. Thus, the fleeing path planning problem is also multiple-path planning problem as shown in Fig. 3.

### III.2 A genetic algorithm with self-configuration chromosomes.

The coding of each chromosome is generated randomly at initial to represent a possible fleeing path. Each chromosome is evaluated by a fitness function in terms of path length and safety. The criteria of path safety is verified by the intersection of the evaluated path and the high-temperature area. And the path length is determined by the number of the grid nodes on the path. Safety. The fitness function is given by

$$F(C) = \sum_{node \in C} S_c(node) \quad (3)$$

where node stands for the nodes on path  $C$ . and  $S_c(n)$  is a safety function with a binary value. The function  $S_c(n)$  is formulized as

$$S_c(node) = \begin{cases} 1 & \text{if } node \notin HT \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where HT is the high temperature area measured by the deployed sensor network.

Based on the definitions of chromosome and fitness functions, the proposed approach features that (1) the optimal chromosome will have highest fitness (2) the chromosome of unfeasible path are discarded in selection. Then the genetic algorithm is performed as follows,

Table 1 The proposed algorithm

<pre> //Genetic Algorithm with self-configured chromosomes //Input: temperature distribution pattern, the origin of fleeing path //Output: fleeing path from the origin to the exit Start Step 1: Path analysis to obtain the low bound of path length <math>L_{min}</math> Step 2: Set the length of initial chromosome, to <math>L_{min}</math>, i.e. <math>l = L_{min}</math> and the obtained solution length <math>k=0</math> Step 3: Initialize the population of chromosomes Step 4: Evaluate the fitness of each chromosome <math>F(C_i) \forall i</math>. Step 5: Operation of Tournament Selection Step 6: Operation of Crossover with single point Step 7: Operation of Mutation with the preset mutation probability Step 8. Evaluate the correctness of the first k nodes. If the first k nodes are correct, adapt the chromosome length, <math>l = l - 1</math> and <math>k = k + 1</math>. Back to step4, else next step. Step 9. If no chromosome selected, back to Step 3 with <math>l = l + 1</math>, Step 10. Output the chromosome with <math>S_c = l</math> End </pre>
---

Defined in Eq. (3), the fitness value increases when the obtained path length is short. Fitness value approaches to zero when the derived path length increased. The safety function yields to one if the corresponding path is safe. In contrast, if the safety function is set to zero, then the path is dangerous. The minimum path length is evaluated by the shortest path from the origin to the destination. All available fleeing path should be longer than the shortest

path with the length of  $L_{min}$ . Evolving from the initial population, the chromosome in generations approaches to the optimal solutions with the optimal fitness. Due to the constant size of the population in each generation, Tournament Selection is deployed to ensure the robustness of the selection operation. The most significant feature of the proposed scheme is the self-configured chromosome. Self-chromosome is with the varying length to search the optimal solution in focus. In Fig. 4, the chromosome is configured with a varying length. Starting from the minimum length, the chromosome is designed to search the shortest path. If the search with the length  $l$  fails, then the chromosome will have longer length to discover possible path solution. Because the path search is in an incremental manner, this strategy is effective to reduce the search time for optimal solution.

### III.3 Design and Implementation of Fleeing Path Guide System

The developed genetic algorithm integrating with wireless sensor network is implemented on a fleeing path guide system. As mentioned, FPG is composed of two major modules; detection module and guide module. Detection module is realized by a ZigBee wireless sensor network and guide module included the proposed SCC and a web server. The architectures of two modules are shown in Fig. 4 and 5, respectively.

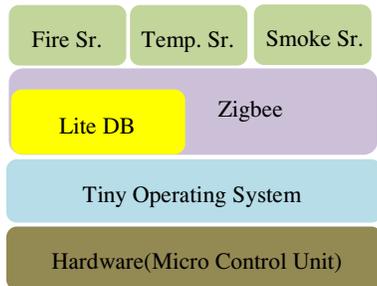


Fig. 4 Architecture of detection module

In the monitored space, the sensed temperature data is forwarded hop by hop to a SQL database for log and analysis. The guide module retrieves temperature distribution data from the database and derives the available fleeing paths. Then the sensor nodes on the derived path will be notified by the guide module to depict the path in lighting and audio.

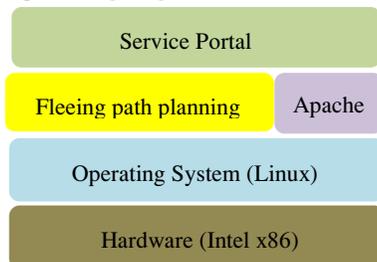


Fig. 5 Architecture of guide module

The flow chart of the fleeing path guide system is as shown in Fig. 6. Upon the detection of a fire in the monitored space, the measurements of smoke sensor and temperature sensor are validated to ensure a fire alarm. If the temperature and smoke alerts are re confirmed, the guide module is started to find available fleeing paths. Addition to the guidance of available fleeing paths, the guidance is also forwarded to the related department for the assistance of rescue activity.

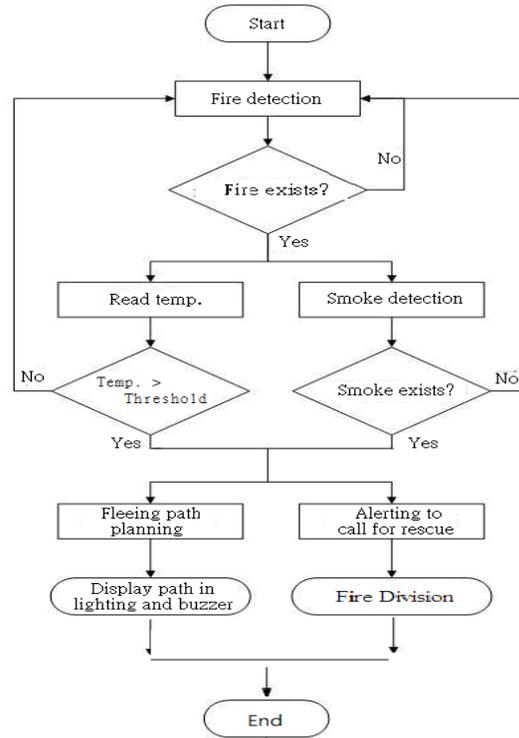


Fig. 6 The flow chart of fleeing path guide system.

### IV. Experiments and Results

The test platform is established in a  $n \times n$  grid space with  $n^2$  temperature sensors, smoke sensors and flame sensors. The software application is developed to offer a user-interface. In the user-interface, there are message area, floor layout and the display of found fleeing paths. The message area shows the received information from all sensor nodes. A simple example of  $5 \times 5$  grid is shown in Fig. 7. In experiments, the test cases with various grid sizes are verified to evaluate the effectiveness, timeliness and reliability. To evaluate the effectiveness, a comparison of the proposed scheme and the original [2] is depicted in Fig. 8. A case of  $50 \times 50$  grid is verified. In this case, the shortest path is composed of 98 movements and the solution space is with  $\binom{100}{50}$  possible solutions. The

results, depicted in a dash line, from the original GA show not only a slow approach to solution traps in a local optimum even that mutation is applied. The reason is that the random search of the original GA can not be dynamically adapted toward the optimum. Besides the invariant chromosome structure leads to a large search space and can not be focused during solution search. The

proposed approach demonstrates a better performance as depict in a solid line. Around 180 generations, the proposed approach reaches the global optimum. Thus, the typical example shows the effectiveness and timeliness of the proposed approach.

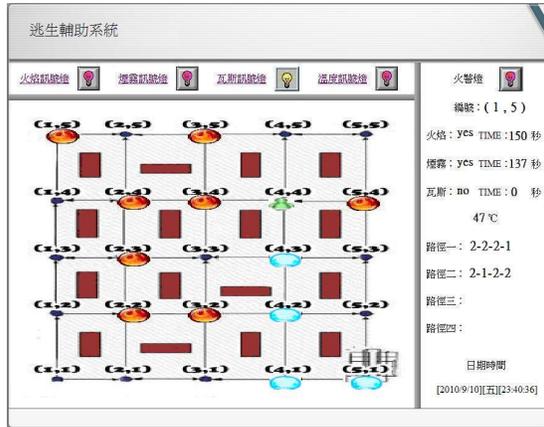


Fig. 7 User interface of the fleeing path guide system.

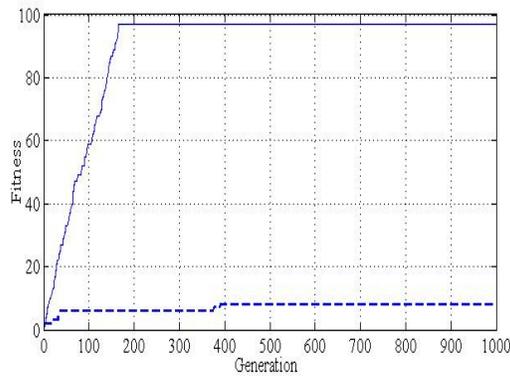


Fig. 8 Searching performance comparison of the proposed approach(solid line) and the original genetic algorithm (dash-line)

Table 2

$n$	30	50	100	200	400	800
solution reach. rate	100	100	100	100	100	98.2

The adaptation of chromosomes of the proposed approach is shown in Fig. 9. From the proposed algorithm as shown in Table1, first a solution analysis is conducted to derive the minimum path length. In this case of 100x100 grid, the shortest path will have 98 movements. As the evolution of solution search, the chromosome structure is adapted to reduce when the number of correct movements,  $k$ , increases. That means the solution search becoming more focused toward the global optimum. The proposed effective and efficient approach demonstrate its feasibility in real applications. To verify the reliability of the proposed approach, the grids with various sizes are

evaluated repeatedly in 30 times to have the solution reachability as shown in Table 2.

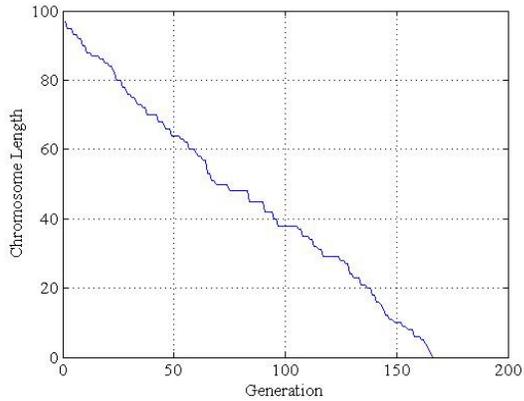


Fig. 9 The adaptation of chromosome length in the proposed approach

A convergence comparison of the proposed approach in cases of various grid sizes is shown in Fig. 10. First, the reliability of the proposed approach is also confirmed. The global optimum solution is discovered in various cases by the proposed approach. Second, the convergence times of the cases depend on the solution space. As the grid size increasing, the solution space is enlarged. Thus, the time to search the optimum solution certainly increase. However, the growth of search-time is not proportional to the grid size. Thus, the computation complexity is feasible.

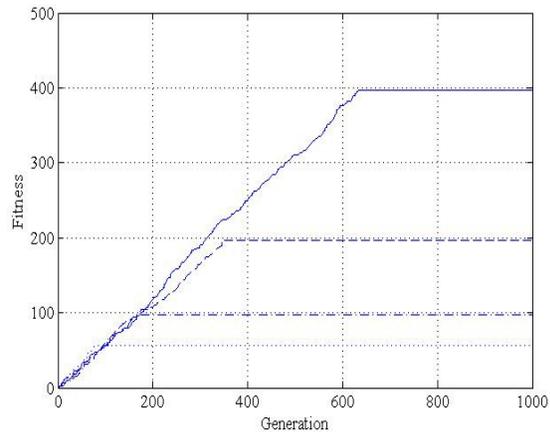


Fig. 10 Convergence comparison of various grid sizes in the proposed approach(dotted-dash line:100x100, dash line:200x200, solid line:400x400)

## V. Conclusion

In this paper, a genetic algorithm with self-configuration chromosome is proposed to discover the optimal fleeing path in a blaze scene. Through the deployed wireless sensor network, the temperature distribution of building and floor is obtained to derive the fleeing path for people rescue. The fleeing path is derived by the proposed approach. The developed approach is also implemented with a wireless sensor network to verify the

function and evaluate the performance of effectiveness, timeliness and reliability. The results show that the proposed approach indeed offers an innovative application. Due to the self-configuration chromosome structure, the search convergence and solution quality are improved significantly.

#### ACKNOWLEDGE

The authors would like to express their sincere thanks to National Science Council, Taiwan, for the financial support under the grants of NSC-98-2221-E-151-029-MY2 and NSC-100-2623-E-006-009-D.

#### REFERENCES

- [1] A. Konar, *Computational Intelligence: Principles, Techniques and applications*. Springer, 2005.
- [2] S. Haykin, *Neural networks: A comprehensive foundation*. Prentice Hall, 1994.
- [3] P. Baldi and K. Hornik, "Learning in linear neural networks: A survey," *IEEE Trans. Neural Networks*, vol. 6, no. 4, pp. 837–858, 1995.
- [4] L. A. Zadeh, "Soft computing and fuzzy logic," *IEEE Trans. Software Eng.*, vol. 11, no. 6, pp. 48–56, 1994.
- [5] M. Dorigo, *Optimization, Learning and Natural Algorithms*, PhD thesis, Politecnico di Milano, Italy, 1992.
- [6] Beni, G., Wang, J. *Swarm Intelligence in Cellular Robotic Systems*, Proceeding of NATO Advanced Workshop on Robots and Biological Systems, Tuscany, Italy, June 26–30, 1989.
- [7] J.D. Farmer, N. Packard and A. Perelson, "The immune system, adaptation and machine learning", *Physics D*, vol. 2, pp. 187–204, 1986.
- [8] J. H. Holland, "Adaptation in natural and artificial systems," The University of Michigan Press, 1975.
- [9] D. E. Goldberg, *Genetic algorithms in search, optimization and machine learning*," Addison Wesley, 1989.
- [10] Z. Bingul, Adaptive genetic algorithms applied to dynamic multiobjective problems, *Journal of Applied Soft Computing archive* , Vol. 7 Issue 3, June, 2007, Elsevier.
- [11] Raghavendra V. Kulkarni, Anna Forster, and Ganesh Kumar Venayagamoorthy, "Computational Intelligence in Wireless Sensor Networks: A Survey," *IEEE Communication Survey and Tutorials*, Vol. 13, Issue 1, 2011.
- [12] I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Commun. Mag.*, vol. 40, no. 8, pp. 102–114,
- [13] E. Cayirci and T. Coplu, "SENDROM: sensor networks for disaster relief operations management," *Wireless Networks*, vol. 13, no. 3, pp. 409–423, 2007Aug.
- [14] S. Wazed, A. Bari, A. Jaekel, and S. Bandyopadhyay, "Genetic algorithm based approach for extending the lifetime of two-tiered sensor networks," in *Proc. 2nd Int. Symposium on Wireless Pervasive Computing ISWPC*, A. Bari, Ed., 2007.
- [15] ZigBee, Alliance <http://www.zigbee.org>
- [16] J. McCulloch, P. McCarthy, S. M. Guru, W. Peng, D. Hugo, and A. Terhorst, "Wireless sensor network deployment for water use efficiency in irrigation," in *Proc. conf. Workshop on Real-world Wireless Sensor Networks (REALWSN)*, Glasgow, Scotland, 2008, pp. 46–50.
- [17] E. A. Basha, S. Ravela, and D. Rus, "Model-based monitoring for early warning flood detection," in *Proc. conf. 6th ACM conf. on Embedded network sensor systems (SenSys)*, New York, NY, USA, 2008, pp.295–308.
- [18] G. Barrenetxea, F. Ingelrest, G. Schaefer, and M. Vetterli, "The hitchhiker's guide to successful wireless sensor network deployments," in *Proc. 6th ACM conf. on Embedded network sensor systems (SenSys)*, New York, NY, USA, 2008, pp. 43–56.
- [19] E. Cayirci and T. Coplu, "SENDROM: sensor networks for disaster relief operations management," *Wireless Networks*, vol. 13, no. 3, pp. 409–423, 2007.
- [20] Scott Niekum, Andrew G. Barto and Lee Spector, "Genetic Programming for Reward Function Search" *IEEE Transactions on Autonomous Mental Development*, vol. 2 no. 2, pp. 83-90, 2010
- [21] K. G. Srinivasa, K. R. Venugopala, L. M. Patnaik, "A self-adaptive migration model genetic algorithm for data mining applications," *Information Sciences*, vol. 177, no. 20, 2007
- [22] R. C. Luo, K. L. Su, and K. H. Tsai, "Fire detection and isolation for intelligent building system using adaptive sensory fusion method," in *Proc. IEEE Int. Conf. Robot. Autom.*, pp. 1777 - 1781, 2002.
- [23] Brad L. Miller, Brad L. Miller, David E. Goldberg, David E. Goldberg, "Genetic Algorithms, Tournament Selection, and the Effects of Noise," *Journal of Complex Systems*, vol. 9, no. 3, pp. 193-212, 1995.
- [24] Shen Wang, Bian Yang and Xiamu Niu, "A Secure Steganography Method based on Genetic Algorithm," *Journal of Information Hiding and Multimedia Signal Processing*, vol. 1, no. 1, pp. 28-35, Jan. 2010.