Pattern Recognition Approach for Swarm Robots Reactive Control with Fuzzy-Kohonen Networks and Particle Swarm Optimization Algorithm

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***Abstract*— A simple reactive control-based pattern recognition approach for swarm robots is presented. Fuzzy-Kohonen Networks is combined with Particle Swarm Optimization (FKN-PSO) for avoiding static and dynamic obstacles, permitting flocking in the group, and efficiently planning the route to the target. A simple algorithm with less computational resources is developed that will produce good performance in terms of ability to avoid the obstacle in an unknown environment, maintain movement, and have a faster time to reach the target. Three simple robots is demonstrated in a series of practical tests in an unknown environment to see the effectiveness of the proposed algorithm. Results showed that the swarm robots successfully performed several tasks, were able to recognize the environment only use seven rules, and produced a small number of resources. The algorithm provides a much faster response to expected events compared to FKN and Fuzzy-PSO and allows the mobile robot to move to the target without collisions.**

***Index Terms*— Pattern recognition; Fuzzy-Kohonen networks; Particle swarm optimization; Optimization.**

I. INTRODUCTION

Swarm robots represent a group of small and simple robots that have limited range of mobility, energy, sensing, communication, and computational resources due to their size and power constraints. Currently, swarm robots have been used in various missions, such as odor localization[1], mobile sensor networking[2], medical operations[3], surveillance, and search-and-rescue[4]. To complete such applications, the implementation is divided into specific tasks, namely flocking, foraging, clustering, searching, aggregation, track formation, navigation, and deployment. Unfortunately, these tasks are very complex and difficult to be resolved individually due to many factors that affect improving their performance; therefore, swarm robots accomplish such missions in unison[5].

How to control a group of robots to make them move as a group toward a target is the most important and fundamental problem. Swarm robot control describes a task of controlling a group of simple robots to avoid some obstacles in the environment and to keep a mobile robot moving in the group in accordance with are determined structure in a dynamic and unknown environment. However, it is very difficult to create a mathematical model of swarm robots because of the uncertainty when interactions occur between the robots and between the robot and the environment.

Actually, swarm robotic systems have the capability to complete an impossible single robot's task, operate in wider range of sensing, actuation distribution in various actions and high fault tolerance, due to the characteristic of decentralization[6].Unfortunately, the swarm robot design has some challenges, the main challenge of which is implementation, e.g., the simple platform of the hardware design, the onboard sensor and processor, fewer computational resources, and a simple communication process.

Swarm robots use the principles of swarm intelligence (SI) approach for controlling the groups of simple robots. They could be a model for observing the natural behavior of insects. They form colonies with individuals that perform different functional roles depending on the needs of the community. The SI approach characteristic consists of an emphasis on decentralized local control and communication and on the emergence of global behavior as are sult of self-organization [7]. Such algorithms have been proposed, including particle swarm optimization, an ant algorithm, bee colony optimization, and a fire-fly algorithm [7].

All the algorithms are good for swarm robot optimization tasks, especially for planning the robot route to reach the target in an efficient manner [8]. Moreover, it is important for swarm robots to respond quickly to its environmental surroundings. However, some sensors cannot sufficiently provide accurate recognition; frequently the measured data contain uncertainties that cause motion errors. Some environmental uncertainty can reduce the performance of the robotic system. Therefore, an approach is needed that can deal with uncertainty in an environmental situation and where robustness properties must be included in the control procedure; however, this will still produce a simple algorithm with low computational resources.

To cope with the uncertainty problems, some intelligent methods have been proposed in robot control, including a fuzzy logic system (FLS),a neural network (NN), and an evolutionary algorithm (EA) [9,10,11,12]. FLS is powerful method in uncertain conditions, but many rules are needed to have good control action. It can be difficult to fine tune the rule for a suitable condition, and this produces a large storage need [10]. The performance of NN depends on its architecture and connecting synaptic weights [11].This technique produces large computational resources and low speed processing due to real-time floating point calculations in the learning process. Another technique, evolutionary robotics-based optimization, offers a new dimension in robotic research [12].The principles of natural evolution and genetics form the basis of EA design, which is usually for the optimization process. However, the EA is very computationally intensive and is not suitable for onboard sensing and processing.

Several studies have been proposed that recognize the mobile robot environment based on precise mapping with a geometric approach. The mapping is designed by using high-quality and powerful sensors [13]. However, in swarm robotic applications the main problem is distributed simple agents with limited physical and resource capacity. Many natural behaviors, including bird foraging, fish schools, and social insects, such as bees, fireflies, and ants, have a unique ability to recognize the environment. In view of robotic research, such activities will become an effective solution for overcoming the main problem, which is how to design swarm robots with inexpensive and simple sensors.

A simple algorithm based on a natural agent is Particle Swarm Optimization (PSO). It can be used to find a solution for an optimization problem in some search space and is an effective technique for swarm robotics search problems [14,15].The PSO algorithm produces a simple code for exploration and enables robots to travel on trajectories that lead to total swarm convergence on some target [15]. Hence, a design for swarm robots with constraints on size, cost, and limited ability to store and process necessary information is desirable.

In the interest of developing swarm robotic control based on a simple platform and with less computational requirements, we propose swarm robot control based on a pattern recognition approach combined with an optimization process, the Fuzzy-Kohonen Network-Particle Swarm Optimization (FKN-PSO) algorithm. The FKN-PSO algorithm design contains an FKN algorithm for controlling a swarm of robots based on the pattern recognition approach, while the PSO algorithm is used for searching and finding the best position of the target. This approach was selected because the FKN produces a simple algorithm [16], the method has the ability to recognize the obstacle pattern [17], and PSO can easily adapt for finding the target [18]. The use of the proposed approach in swarm robots was developed based on human expert knowledge, heuristics, and experience. The effectiveness of the FKN-PSO approach will be compared to the FKN and Fuzzy-PSO approaches in terms of the time traveled to the target and computational cost.

II. SUPERVISED DISTRIBUTED-PSO ALGORITHM DESIGN

Problems with swarm robotic control can roughly be divided into three major issues: first, the swarm robots must recognize the environment in order to know its position; second, they must recognize obstacles in order to navigate safely; and last, they must maintain the formation of the group when they are moving in several environments [16]. However, to overcome such problems, swarm robots have basic limitations, including a limited physical onboard sensor and processor and less computational resources [17].

Hunts Berger and Ajjimarang See [19] proposed a hybrid technique that is the result of integrating fuzzy logic and the Kohonen network. In that approach unsupervised learning is used for clustering tasks. However, the learning process requires intensive procedures and therefore produces a high computational cost [20].This means a large storage capacity is needed to finish the learning process. To reduce the learning rate, the supervised approach in the Kohonen network is used. The combination of Kohonen networks with supervised learning and fuzzy logic with self-organizing results in automatically updating the size of the neighborhood during the learning process [17].

A. FKN-PSO Design

In this approach, environmental classification is required by the robot to create some patterns. Seven types of obstacle configurations utilized in this research are shown in Figure 1. The combination process of fuzzification with seven environmental patterns, produces a simple algorithm and does not need to consider another obstacle configuration, which is the main purpose of the membership layer. It generates simple control rules compared with conventional fuzzy control methods [17]. In this paper, three simple mobile robots are used with infra-red sensors onboard in each robot to recognize the environmental pattern and as an input to the FKN. To reduce the computational resources and fast response in the control action, only seven rules are utilized. In order to make the swarm robot-based FKN algorithm flexible to explore the environment, PSO is used to optimize the route for moving to the target. In the FKN algorithm, especially environmental patterns number 4, 5 and 6, they can become a static or dynamic obstacles; due to swarm robots move in the group.

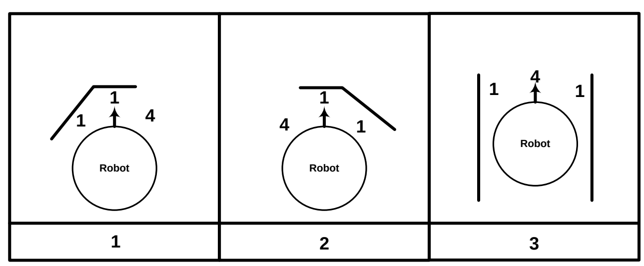


Figure 1: Seven environmental patterns for swarm robots to recognize

To achieve real-time reactive swarm robots control, one strategy would be to construct perfect mapping between the input sensor data and appropriate control actions. However, this is very complicated and highly nonlinear. Therefore, a rules table was established in this approach according to heuristic experience. Due to, redundant rules would increase the computational resources and produce a longer time for the fuzzy process. The rules table was constructed by exploiting the sequence of environmental patterns in accordance with motor speed levels, as shown in Table 1.The basic idea of the FKN approach is to make the IF part of a rule be the pattern class and the THEN part be the reference to left motor speed (*Vleft*) and right motor speed (*Vright*) values; the FKN process then calculates a resultant motor speed command. Based on table 1, the FKN algorithm create only seven rules base for making control decision. Our previous experimental result have been implemented in single robot [16] and swarm robots [17]. The research produce good performance in terms of computational resources, time travelled and overcome the local minima [16]. However, it doesn't use target position, therefore in this paper the FKN algorithm is combined with simple PSO algorithm to make optimization route for finding the target.

Table 1
The FKN rules table

Number of Rules	IF Part Prototype Pattern			THEN Part Reference of motor speed Vleft (%)	Vright (%)
1	1	1	4	80	30
2	4	1	1	30	80
3	1	4	1	50	50
4	4	1	4	25	25
5	1	4	4	70	25
6	4	4	1	25	70
7	4	4	4	35	35

B. *Swarm Robot Control Algorithm*

A simple block diagram control of the proposed algorithm is described in Figure 2. The system receives input from two sensors, the infra-red sensor for environmental pattern detection and the target sensor for moving to the goal. Output from the FKN includes obstacle avoidance and flocking, and output from the PSO is target seeking. Two parameters are determined by the swarm robots: heading to the target and the speed of the motor. The FKN-PSO algorithm is activated alternately in accordance with the results of the sensor detection.

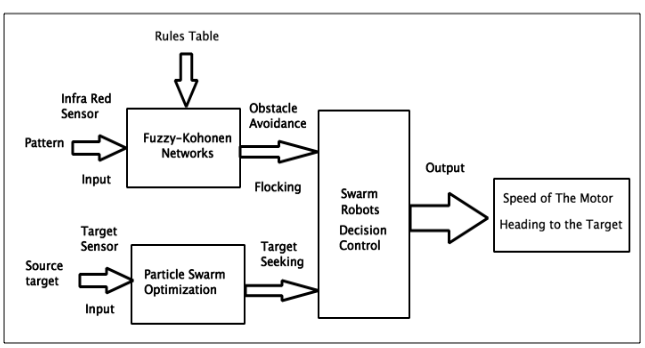


Figure 2: Block diagram showing swarm robot control

The heuristics approach are combined into a fuzzy neural network to achieve the desired pattern-recognition results. The FKN structure is adopted for the desired pattern-recognition function. FKN is a three-layered, pattern-classification network and is shown in Figure 3. The network trained a prototype pattern associated with each class. In the conventional neural network, all these prototype patterns are set to the weights in the distance layer, but in the FKN process the weights are assigned instead of being trained.

For simplicity and to reduce the computational time and resources, the clusters are known in advance. It is known from previous study that assigned patterns derived from actual experimental data and human experience produce good results in computational time and resources [16, 17, 20]. This approach has been studied previously by using a single robot [16, 17] and is currently developed by combining with PSO for swarm robot control. During the process of the FKN-PSO algorithm, the task priorities are obstacle avoidance. Moving in a group or flocking is not a priority because if one robot detects a target, then all the robots will move together toward a position that has been achieved by the target sensor. The PSO algorithm actively finds the target position only when the time the sensor targets the active position.

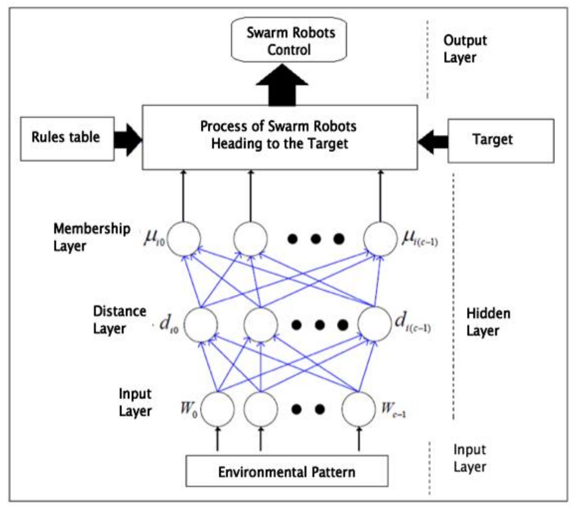


Figure 3: Fuzzy Kohonen network structure [16]

The PSO algorithm process is initialized by a group of random particles, *N*. The i_{th} particle is represented by its position as a point in an S-dimensional space, where *S* is the number of variables. The overall of process, the i_{th}particle monitors three values: current position$x_i = (x_{i1}, x_{i2}, ... , x_{is})$, the best position it reached in previous cycles $p_i = (p_{i1}, p_{i2},...., p_{is})$, and flying velocity $v_i= (v_{i1}, v_{i2},...., v_{is})$.In this research, the number of robots is equal to the number of particles(i). Each robot has the best position or particle best (P_i), but all robots have only one best particle, or global best(P_g). When the swarm robots move to find the target, the robots sensor detects in all directions. The sensor value is compared to each initial particle best of the robots' position $f(x_i)>f(P_{best})$, and this is compared to the global best $f(x_i)>f(g_{best})$; the robots then move toward the target. The process repeats to find the target in an optimal solution. In each time interval (cycle), the position (P_g) of thebest particle (g) is calculated as the best fitness of all particles.Accordingly, each particle updates its velocity $v_i$to catch up with the best particle *g*, as follows:

$$v_i^{k+1} = w_i * v_i^k + c_i * r_1 * \left(p_i^k - x_i^k\right) + c_2 * r_2 * \left(p_g^k - x_i^k\right), \tag{1}$$

$$x(k+1) = x(k) + v(k+1) x_i(k+1) = x_i(k) + v_i(k+1). \tag{2}$$

In this research, collision avoidance is essential behavior because each robot in the swarm becomes a moving obstacle to the other robots. When robot x_i at position p_n, calculates the next position to move to p_{n+1}, x_i must be determined. If any other robots are on the path, then p_n moves to p_{n+1}. But if a potential collision is detected with another robot x_j, the PSO algorithm will calculate a new random direction for x_i. In that situation, x_i changes to a new position, and the algorithm will check robot collision again until the path is free.

III. EXPERIMENTAL RESULTS AND ANALYSIS

Practical swarm robots reactive control experiments were conducted employing three self-constructed mobile robots. They are of cylindrical shape, with diameters about 20 cm. Two drive wheels are placed at the ends of its central axis, and one free caster at the front and for balance. The drive wheels are controlled by using a DC servo motor with a maximum travel speed of about 25 cm/s.

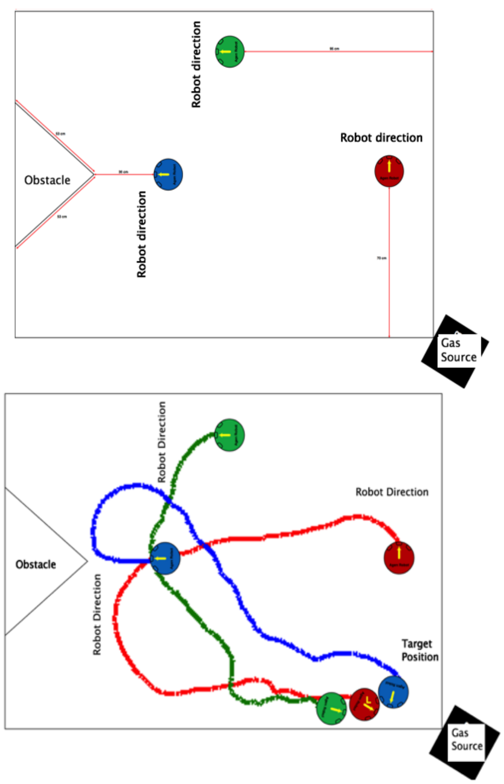
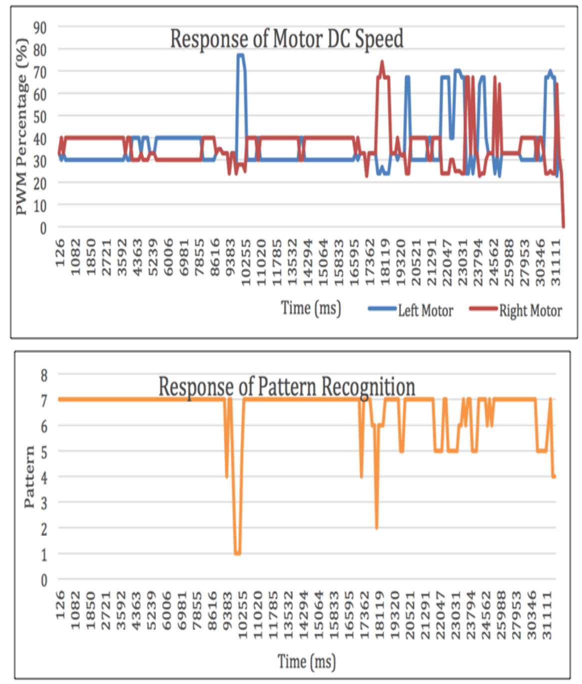
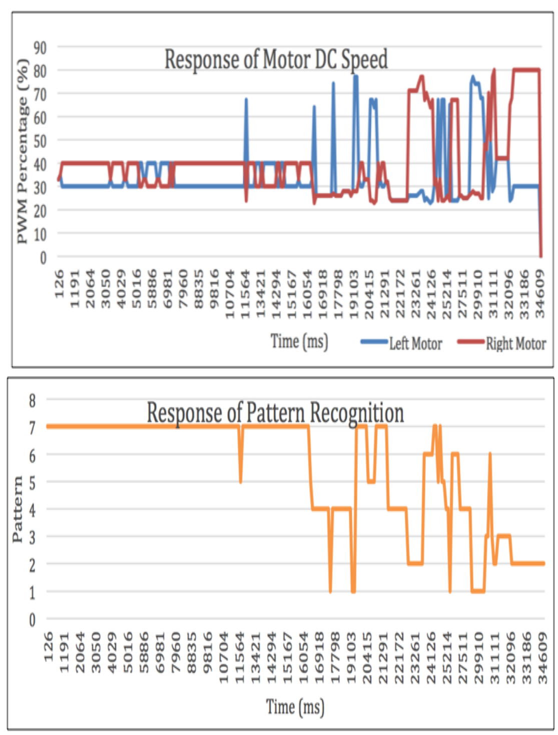


Figure 4: Swarm robot trajectory in a simple environment

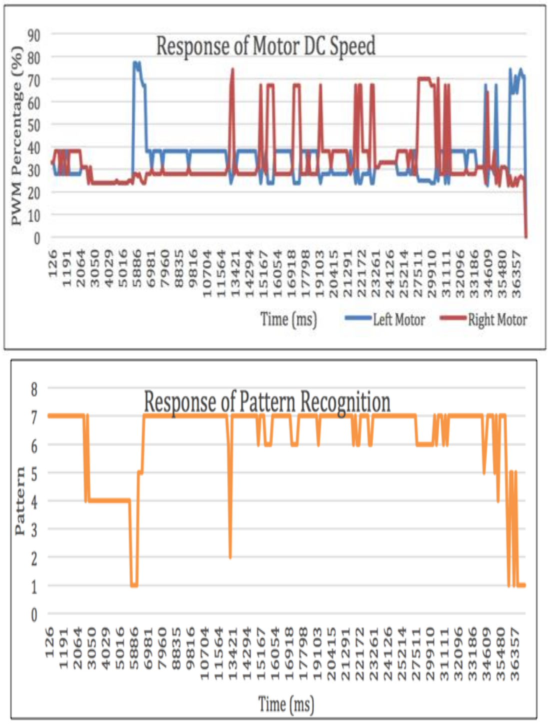
In the experiments, only the start and target positions were specified. The swarm robots had to find a collision-free path to the target employing onboard sensory information. Figure 4 presents the experimental results of the proposed FKN-PSO control algorithm. In that figure, the label ‘robot direction’ denotes the start point and the label ‘gas source’ denotes the target position. The three robots have three colors, red is Robot 1, green is Robot 2, and blue is Robot 3. The executed swarm robots’ route is depicted with a sequence of circles, where the trajectory of the mobile robot is plotted for every two sampling periods.



(a) Environmental recognition of Robot 1



(b) Environmental recognition of Robot 2



(a) Environmental recognition of Robot 3

Figure 5: Swarm robot recognition for a simple environment

The recorded swarm robots' trajectory showed that each robot can avoid obstacles safely and in an efficient manner. Figure5 presents the recorded speed control of both wheels in this work. Speed control of the DC motor was about 30%–80% of the maximum speed. The values are obtained from the duty cycle control of each motor. They can be used to check the maneuvering of the swarm robots as they encounter obstacles. This indicates whether each obstacle pattern detected by the sensor will change the control signal of the motor, which causes changes in the movement of each swarm robot. Consequently, a smooth trajectory is executed for obstacle avoidance and traveling to the target. The proposed algorithm provided good reactive control, and the swarm robots produced optimal performance.

From Figure 5, the seven pattern configurations embedded in the FKN algorithm area static obstacle, but a moving obstacle is considered for measuring the performance of the swarm robot. The FKN algorithm will be active at the condition of environmental patterns 1 to 6, in which situations swarm robots take action to avoid an obstacle and flock in the group. This remains a priority in the FKN-PSO process. However, if environmental pattern 7 occurs, the swarm robots check the target by the sensor. If the sensor target is active, it will enable the PSO algorithm. If one of the robots detects the target source, the robot goes to the source and broadcasts the target position to the other robots.

In this research, the proposed algorithm were compared to the FKN and Fuzzy-PSO approach. The results showed FKN-PSO produce less time to find and reach the target and reduce the number of rules base and resources compared to FKN and the Fuzzy- PSO approach. Moreover, the control signal output from the motor was more stable, due to it generates control action based on the prototype pattern and according to the reference of the motor speed change. However, Fuzzy-PSO generates control actions in accordance with changes in sensors detection. In that situation each rule is activated in relation to the sensors detection. It causes the motor speed output change every time. But if only FKN algorithm is used, the swarm robots hard to communicate each other to find the target and it increase the time of control process.

Table 2
FKN, Fuzzy-PSO, and FKN-PSO performance in a simple environment

Parameter	FKN	Fuzzy-PSO	FKN-PSO
Time to target detection(sec)	17	10	2
Time to reach target(sec)	43	30	14
Rule base	21	27	7
Resources(Kbytes)	15	45	42

IV. Conclusion

A heuristic pattern recognition approach to reactive control for swarm robots based on real-time sensory information has been developed and successfully implemented on three simple swarm robots. The FKN approach is combined with PSO to optimize the target search and for keeping the swarm robots in a group when they find the target. By employing a small number of rules only seven rules base, satisfactory performance has been achieved. In this research, the FKN and Fuzzy-PSO approach were used as a benchmark for comparing the proposed approach. By using the FKN-PSO algorithm, the computational resource is reduced, and this enhances the real-time performance of swarm robot reactive control. Many aspects of this method are worthy of further investigation. Although the proposed approach can cope with moving swarm robots as well as stationary obstacles, more accurate perception sensors are required for more complex environmental configurations. On the other hand, prototype mapping could be optimized to play a more important role in the algorithm.

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References

[1] Marjovi, A., and Marques, L. , "Optimal spatial formation of swarm robotic gas sensors in odor plume finding," *Autonomous Robots*, vol. 35, no. 2–3, pp. 93–109, 2013.

[2] Berdahl, A., Torney, C.J., Ioannou, C.C., Faria, J.F., and Couzin, I.D. , "Emergent sensing of complex environments by mobile animal groups," *Science*, vol. 339, no. 6119, pp. 574–576, 2013.

[3] Haidegger, T., Barreto, M., Gonçalves, P., Habib, M.K., Ragavan, S.K.V., Li, H., Vaccarella, A.,Perrone, R., and Prestes, E., "Applied ontologies and standards for service robots, Robotic Autonomous System,", vol. 61, no.11, pp. 1215–1223, 2013.

[4] Gunn,. T and Anderson, J., "Dynamic heterogeneous team formation for robotic urban search and rescue," *Journal Computer System Science*., vol. 19, no. 3, pp. 22–31, 2015.

[5] Bayindir, L. *A review of swarm robotics tasks. Neurocomputing*, 2015.

[6] Senanayake, M., Senthooran, I., Barca, J. C., Chung, H., Kamruzzaman, J., and Murshed, M., "Search and tracking algorithms for swarms of robots: A survey," *Robotics and Autonomous Systems*, vol.75, pp. 422–434, 2016.

[7] Lefranc, G., "Colony of robots: New challenge," *International Journal of Computers, Communications and Control*, pp. 92–107, 2008.

[8] Blum, C., and Grob, R., "Swarm Intelligence in Optimization and Robotics," *In: Springer Handbook of Computational Intelligence*, pp. 1291–1309, 2015.

[9] Venayagamoorthy, G.K., Grant, L.L., and Doctor, S., "Collective robotic search using hybrid techniques: Fuzzy logic and swarm intelligence inspired by nature," *Engineering Applications of Artificial Intelligence*, vol. 22, no. 3, pp. 431–441, 2009.

[10] Castillo, O., Martínez-Marroquín, R., Melin, P., Valdez, F., and Soria, J. ,"Comparative study of bio-inspired algorithms applied to the optimization of type-1 and type-2 fuzzy controllers for an autonomous mobile robot.," *Information Sciences*, vol. 192, pp. 19–38, 2012.

[11] Jolly, K.G., Ravindran, K.P., Vijayakumar, R., and Kumar, R.S., "Intelligent decision making in multi-agent robot soccer system through compounded artificial neural networks," *Robotics and Autonomous Systems*, vol. 55, no. 7, pp. 589–596, 2007.

[12] Kala, R., "Multi-robot path planning using co-evolutionary genetic programming," *Expert Systems with Applications*, vol. 39, no. 3, pp. 3817–3831, 2012.

[13] Yamada, S., "Recognizing environments from action sequences using self-organizing maps," *Applied Soft Computing*, vol. 4, pp. 35–47, 2004.

[14] Senanayake, M., Senthooran, I., Barca, J. C., Chung, H., Kamruzzaman, J., and Murshed, M, "Search and tracking algorithms for swarms of robots: A survey," *Robotics and Autonomous Systems*, vol. 75, pp. 422–434, 2016.

[15] Di Mario, Ezequiel, Navarro, I., and Martinoli, A., "Distributed learning of cooperative robotic behaviors using particle swarm optimization," *In :Experimental Robotics*, pp. 591–604, 2016.

[16] Nurmaini, S., "Memory-based reasoning algorithm based on fuzzy-Kohonen self organizing map for embedded mobile robot navigation," *International Journal of Control and Automation*, vol. 5, no.3, pp. 47–63, 2012.

[17] Nurmaini, S., Zaiton, S., and Firnando, R, "Cooperative Avoidance Control-based Interval Fuzzy Kohonen Networks Algorithm in Simple Swarm Robots," *TELKOMNIKA*, vol. 12, no. 4, pp. 795–810, 2014.

[18] Nurmaini, S., Tutuko, B., and Rahman, T.A, "A new navigation of behavior-based olfactory mobile robot," *In:Applied Mechanics and Materials*, vol. 446, pp. 1255–1260, 2014.

[19] Huntsberger, T.L., and Ajjimarangsee, P., "Parallel self-organizing feature maps for unsupervised pattern recognition," *Int. Journal General Systems*, vol. 16, no. 4, pp. 357–372, 1990.

[20] Tsai, C.C., Chen, C.C., Chan, K.C., and Li, Y.Y., "Behavior-based navigation using fuzzy kohonen clustering network for mobile service robot," *International Journal of Fuzzy Systems*, vol. 12, no. 1, pp. 25–32, 2010.