Available online at www.sciencedirect.com

ScienceDirect

Procedia Manufacturing 35 (2019) 755–761

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

2nd International Conference on Sustainable Materials Processing and Manufacturing

(SMPM 2019)

A Multi-Objective Optimization Approach to Robot Localization of Single and Multiple Emission Sources

Samuel Obadan, Zenghui Wang*

College of Science, Engineering and Technology, University of South Africa, Florida 1710, South Africa

Abstract

A growing research axes in the field of artificial intelligence understudies the corporate behavior that emerges as a result of interactions among non-complex multi-agent robots and the potential of this behavior in providing sustainable solutions to the multi-source localization problem. While locating a single emission source or single target location has been treated extensively, there has been comparatively little emphasis on locating multiple target locations. Although some partial solutions to the general problem of localizing multiple emission sources do exist, they however are not integrated in an adhesive synergy and also lack clear recommended strategies to proceed with a search after a source/target is found. The missing piece of the multisource localization puzzle is the absence of theoretical foundations for progress (after a source is found), convergence, and termination of the search operational algorithm. Cooperation among multi-agents could be active (agents acknowledging each other) or inactive (agents oblivious of each other). In this paper, the authors investigate the potency of multi-objective optimization on a machine learning algorithm (the artificial neural network) for a swarm of robots by leveraging on their basic yaw and thrust actuators in order to achieve collaborative control (group behavior) amidst localization of multiple emission sources. The empirical results from our simulations are promising.

Peer-review under responsibility of the organizing committee of SMPM 2019.

Keywords: Genetic algorithm; Dynamic programming; Evolutionary Neural networks; Cooperation; Search optimization

* Corresponding author. Tel.: +27-11-4713513
E-mail address: wangzengh@gmail.com

2351-9789
Peer-review under responsibility of the organizing committee of SMPM 2019.
10.1016/j.promfg.2019.06.020

1. Introduction

It is relatively instinctive to perceive cooperation in terms of a group of robots collaborating for the purpose of accomplishing a particular task. In the active cooperation, a group of robots exhibit cooperate behaviour by acknowledging each other. While in the non-active (oblivious) cooperation, a corporate behaviour emerges as each robotic agent embarks on its immediate goal, without acknowledging each other [1]. An indelible requirement for active cooperation is the ability of a robotic agent to differentiate between its peers (other agents) and its immediate environment. However, when robots show active cooperation by acknowledging each other, it doesn't suffice to conclude that there exists communication between robots. An example of such an instance can be sited on a robot soccer platform whereby a robot passes a ball to another robot (team mate) within its view in the absence of the goal. This behaviour is exhibited irrespective of the robots lack of awareness of the position of other team mates outside its view. On the other hand, because the non-active (oblivious) cooperation requires little or no sensing, it has attracted remarkable interest in the robotic research community [2].

This paper presents a potential leverage of non-active cooperative multi-agent robots for localizing multiple emission sources. We also identify a vital research axes in the field of sustainable manufacturing systems with respect to unveiling a methodology for oblivious collaboration among robotic agents in localizing potentially hazardous emission sources simultaneously. While locating a single emission source has been treated extensively [1], there has been comparatively little emphasis on locating multiple emission sources/target locations. Although some partial solutions to the general problem of localizing multiple source locations do exist, they however are not integrated in an adhesive synergy. For example, obstacle avoidance models derived from swarm control, which treats robots and obstacles as repulsive objects shows some of the most promising implementations [3, 4, 5]. The raciest example can be attributed to swarm partitioning in which subgroups form within the swarm, while searching for nearby sources also referred to as adaptive local partitioning of the Glowworm Swarm Optimization (GSO) algorithm [6]. Unfortunately, the literature lacks clarity of strategies needed for proceeding with a search after a source or target location has been found. Apparently, the task of locating multiple emission sources with mobile robotic systems is distinctly different from that of observing target locations with mobile robotic systems especially in the field of computer vision and surveillance. In the case of the later, all emission sources in the area are tracked and in most cases, source locations are known from the beginning of the mission. The task is basically to allocate network resources to track multiple known targets simultaneously [7, 8]. However, in the case of the former, the task is to allocate network resources to find an unknown number of sources simultaneously. The strategies for the two scenarios are algorithmically and computationally different.

In this paper, the authors develop and test an algorithm for the former, leveraging a machine learning algorithm (the feed forward artificial neural network) for a swarm of robots with the elicit Non-Dominated Sorting Genetic Algorithm (NSGA-II) as an optimizer for localizing multiple emission sources. This ingenious approach promises solution to the missing piece of the multisource localization puzzle of progress (after a source is found), convergence, and termination of the search operational algorithm.

2. Problem Specification

Currently, the existing multisource localization strategies provide no clear recommended strategies to proceed with a search after a source is found. The missing piece of the multisource search puzzle is to provide theoretical foundations for progress (after a source is found), convergence, and termination of the search operational algorithm. Although there exists substantial contribution by the "attractant/repellent swarm" model of Gazi and Passino [5] its operation is however limited to single source searches.

The computational complexity of the solution, the nature of source, and the unpredictable environmental variables are some of the issues which affect the performance of a multisource solution. [9, 10, 11] An attempt to circumvent these problems is the implementation of the Bayesian Occupancy grid algorithm. This algorithm proffers an almost optimal solution to the multisource problems. Nevertheless, this algorithm lacks adequate comparative analysis against the backdrop of biological inspired algorithms.

However, the Bayesian algorithm has a computational complexity trade off (in terms of data storage, local and/or global communication overhead, and algorithmic computation) which presents a major drawback. [1]

In addition, there exist the questions of how to choose a set of dependent and independent variables and how a comparative analysis should be conducted. An establishment of a common set of variables such as (initial distribution of gradient sources and robots, presence and location of obstacles, etc) could impede the implementation of a standardized structure to compare and contrast the different algorithms and weigh their merits and demerits for disparate implementations.
In this paper, the authors propose an algorithm using dynamic programming (for simulating multiple gradient sources) and multi-objective optimization (NSGA-II) optimizer on artificial neural networks for a pair of robots by leveraging on their basic yaw and thrust actuators in order to achieve oblivious collaborative control (group behaviour) amidst localization of multiple emission sources. This approach presents promising solution to progress, convergence, and termination problem of localizing multiple emission sources.

3. METHODOLOGY

3.1 ENNs (Evolutional Neural Networks) using Continuous Variables

Every autonomous mobile robot must be able to perceive its environment while navigating without colliding with obstacles within its environment. With the implementation of ENNs, the robot was equipped with sensors (internal state which is used to keep track of gradient source intensity) which became inputs into its neural network (brain) with which it could perceive his environment [12, 13,14, 15, 16].
The neural network was designed as a multi-layer network with 5 inputs, 2 output neurons and 20 neurons in the hidden layer. Each neuron is activated using the sigmoid activation function. The output of the network determined the robot trajectory. If output 1 is the highest, the robot thrust forward one step else it turns (rotate left or right) by 0.1 radians. The weights of the neurons (chromosome) is stochastically determined at instantiation of the first run between [-1, +1] range. After 7500 frames (clock cycles) (the end of the first run), algorithm then filters out the best performing robots by performing multi-objective optimizer precisely the NSGA-II algorithm for selection, crossover, and mutation on the array of the neural weight vectors.

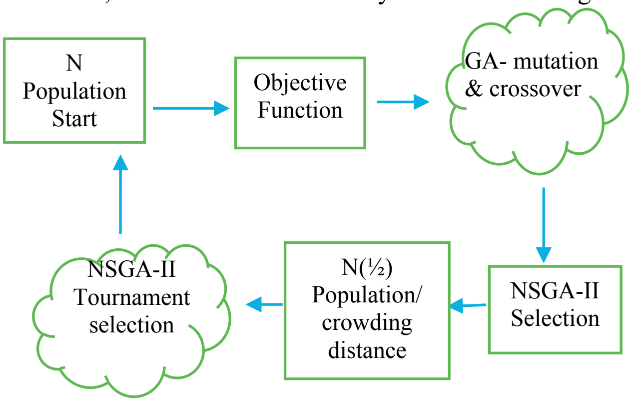

Figure 1.0 Optimization architecture pipeline

A population of 100 pairs of robotic agents were trained using a single neural network structure for both pairs. Fig. 1.0 above shows the optimization pipeline after every 7500 clock cycles. The new array of chromosomes (fitter weights) are fed back into the neural network as 'generation next' [17, 18].
The entire process is iterated until there is convergence, or desired number of generations has been attained, or there is lack of significant improvement in the performance.
Each sensor returns a value between [-1, +1] range based on the cell segment of the environments its tip is touching. If it's on an obstacle, it returns -1 else it returns a continuous variable within the predefined range based on the perceived gradient source value. Two conflicting properties determines the fitness of each robot, thus the use of the multi-objective approach. These properties are, exploration, and Homing. A highly explorative robot may ignore the mission of homing on gradient source in good time while a robot with a high bias for homing on target may lose the capacity to localize more than one emission sources. Consequently, the NSGA-II algorithm attempts to find the Pareto-optimal front that balances these two objective functions by minimizing exploration and maximizing homing.

This implementation considerably improved the performance the of search algorithm.

3.2 Dynamic programming (DP) approach for modelling multiple gradient sources

Dynamic programming implementation for path planning usually involves finding an optimal policy (orientation) from every valid node (unoccupied or obstacle free node) on the grid to the goal node. An invalid node on the grid is a node that represents an obstacle.
Given the (6 x 6) grid world as an example shown in Fig 2.0 below, DP presents an intuitive model for representing multiple gradient sources. The zero locations are indicative of the originating positions of the gradient sources thus having the highest gradient concentrations. The increasing values are indicative of diminishing concentration strength as we move away from the gradient sources. However, this approach assumes the absence of a dead space (locations without any gradient signal) within the search space.

3	2	1	2	//////	5
4	/////	0	1	////////	4
5	/////	1	2	/////////	3
4	3	2	2	1	2
5	///////	////////	1	0	1
5	4	3	2	//////////	2

Figure 2.0 modelling multiple emission sources on a grid world.

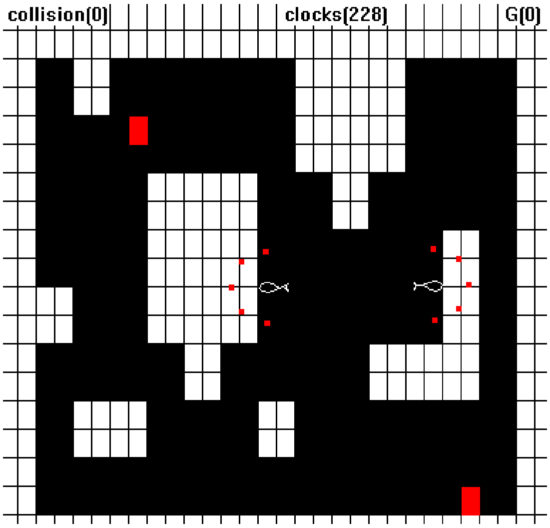

Figure 3.0 Scenario 1 the robotic agent equipped with 5 sensor inputs into its feed-forward neural network (brain) with 2 gradient sources in RED.

3.3 Calculating Fitness values (F1 and F2)

The following equations where used for calculating the homing (F1) and explorative fitness score (F2) respectively. It's important to note that in robotic applications, it is intuitive to view the grid world and the task as the objective function. However, the decision space constraints for the weighted values are within the [-1, +1] range.

$$f1 = \sum_{i=1}^{N}\sum_{j=1}^{n}\frac{1}{C_j + 1}\ (K) \tag{1}$$

$$f2 = \sum_{i=1}^{N}\sum_{j=1}^{n}(V_j) \tag{2}$$

where,
C_j is the estimated Euclidian distance from source location derived from the sum of all sensor readings.
K is a large constant (typical value 1000)
n is the number of sensor readings
N is the duration of clock cycles (typical value 7500)

V_j is the sum of all sensor values in visited cells

3.4 RESULTS

In Senario1 (Fig. 3.0), the agents were able to localize both emission sources simultaneously. By keeping track of the homing score, we could deduce from our objective space, the exact solution among the feasible solutions, responsible for completing the task. At the end of the 3rd generation, the task of localizing both emission sources were completed at 5000 clock cycles. The algorithm asymptotes at the 5th generation, completing the mission at 1250 clock cycles. It was observed that the agents split apart to find both sources.

In Senario2, (emission sources are placed at the bottom edges of the grid world) the agents were able to localize both emission sources also. At the end of the 3rd generation, the task of localizing both emission sources was completed at 3300 clock cycles. The algorithm asymptotes at the 5th generation, completing the mission at 2180 clock cycles. Again, it was observed that the agents split apart to find both sources.

Also in Senario3, (emission sources are placed at the top right and bottom left edges of the grid world) the agents were able to localize both emission sources. At the end of the 3rd generation, the task of localizing both emission sources was completed at 2350 clock cycles and asymptotes. Again, it was observed that the agents split apart to find both sources.

In our final simulation - Scenario 4, (emission sources are placed at the top and bottom right edges of the grid world) the agents were able to localize both emission sources at the end of the 3rd generation. The task of localizing both emission sources was completed at 4550 clock cycles. The algorithm asymptotes at the 5th generation with the same number of clock cycles. However, it was observed that only one agent took responsibility for finding both sources. This behaviour suggests the potency of this algorithm in providing a theoretical foundation for progress after an emission source is found.

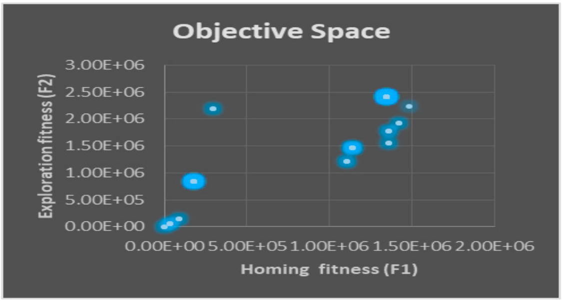

Figure 4.0 the Pareto-optimal front for Scenario 1

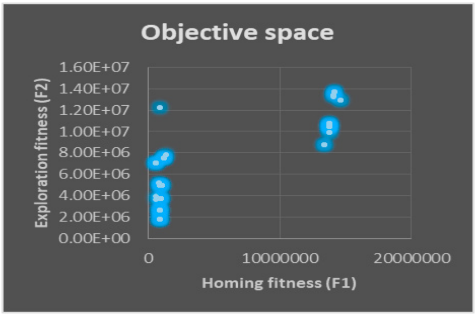

Figure 5.0 the Pareto-optimal front for Scenario 2

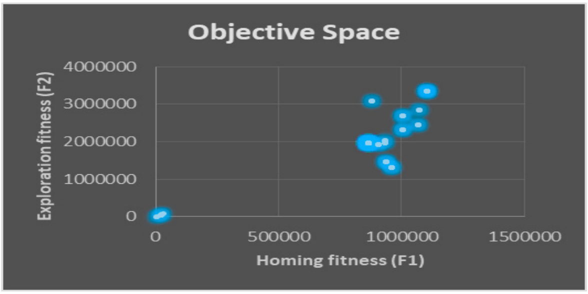

Figure 6.0 the Pareto-optimal front for Scenario 3

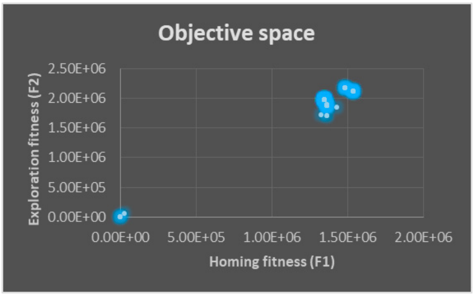

Figure 7.0 the Pareto-optimal front for Scenario 4

In (Fig. 4.0 -7.0) we observe the algorithm's migration of the best solutions towards the Pareto-optimal front (as shown in the top right clusters). This is as a result of the NSGA-II optimizer's attempt to find the most suitable solutions that limits excessive exploration while homing in on the source location. It is interesting to note that the Pareto-optimal front tend to migrate towards the top right rather than the bottom right because intuitively, homing is not possible without a considerable amount of exploration.

4. A Comparative Analysis with two Existing biological Models

Table 1.0 Adapted Summary of multi-search options and their characteristics.

	GSO	PSO	Proposed Model
Swarm size	1000	10	2
Source Number	100	5	2
Source type	Generic	Chemical	Generic
Source mobility	Mobile	Fixed	Fixed
Variable source intensity	Yes	No	Yes
Dead space	No	Yes	No
Communication range	Local	Local	Global
Agent deployment	Random, centre, corner	Corner	Centre
Computational complexity	Low	Medium	Medium
Obstacle avoidance	Sensory based	Artificial repulsion	Artificial repulsion
Sensing requirement	Signal intensity	Other Robots, obstacles	Signal intensity
Proceeding after source is found	None	Source collection	Source collection
Theoretical foundations	Clustering behaviour	None	Multiple source profiles

Source: Kathleen Mcgill, Stephen Taylor 2011 [1]

From Table 1.0, we see some of the features of two biological inspired model and how each model attempts to tackle the multisource localization problem. The swarm size shows the total number of robots deployed in each experiment. The source number indicates the total number of emission sources to be located by the robots. The type of sources falls into two major categories: Generic or chemical. While the PSO model is tailored towards chemical sources, the GSO and our proposed model uses a Generic model for emission plumes. In our proposed model, the source was simulated without the presence of a dead space (zero signal spots). Thus robots that are instantiated from dead space may roam (depending on the implemented model), until they sense a signal source.

Chemical sources are also referred to as gradient sources such that robots could sense the presence of the source based on their spatial proximity from the source target. Also, because PSO utilized plume modelling, the use of chemical source was suitable for simulating the presence of a background flow.

Source mobility suggests the attribute of each source changing positions. They could either be mobile or fixed. Although fixed sources was used in simulating our proposed model, the proposed model has the potential of incorporating the localization of mobile or drifting sources.

The communication method utilized by the robots could either be local or global. In the local communication, the robots share information among themselves which influences their decisions as implemented by the GSO model. In our proposed model, the communication model could be classified as global because each robot's motion updates the state of the grid world which also influences the trajectory of the robot. There is no information sharing between robots, however, they are share a single artificial neural network frame-work and as a result, meaningful oblivious collaboration is achieved.

In addition, the mission could be instantiated with all robots deployed at the corner of the grid world, or at the middle, or at random. The middle was adopted for all simulations.

The complexity of the system software and hardware requirement needed for the implementation of each model is referred to as the computational complexity. The computational complexity is determined by the data storage required, the local/global communication overhead, and the complexity of the algorithm. Leveraging these indicators, we could then place the complexity of the system into any one of the 3 categories: LOW, MEDIUM, and HIGH. If any two of the stated indicators are low, then the computational complexity is classified as LOW. In the same vein, if any two of the stated indicators are high, then the computational complexity is classified as HIGH.

Like the PSO model, our proposed model implement artificial repulsion for obstacle avoidance. Other biologically inspired models like GSO, implement sensory based obstacle avoidance.

One significant contribution of our proposed model to the multisource localization problem is the ability to proceed with a search after a target is found and also progress the search to convergence and termination.

Although, source collection mechanism was deployed in our simulation, just like the PSO, we observed the potential for progress even in absence of degrading sources. Partitioning indicates the presence of the mechanism (as found in the GSO model), to partition a swarm into sub-groups in an attempt to localize multiple sources. This aspect remains part of our ongoing research such that multiple agents could learn to form sub-groups as they progress with the search.

5. CONCLUSION AND FUTURE DIRECTION

In this paper, the authors unveiled an ingenious model for solving the multisource localization problems of progress (after a source is found), convergence, and termination of the search operation. The proposed model combines the strengths of the NSGA-II Multi-objective algorithm with the elegance of a feedforward evolutionary neural network. This model revealed a possible axis towards a sustainable optimization strategy for finding multiple emission sources in manufacturing environments. A comparative analysis on the performance of our proposed model with two existing paradigms such as the PSO and the GSO showed promising results.

Although our proposed model has achieved some success, its potential has not been fully investigated. It would be interesting to investigate how the localization of mobile emission sources would affect the dynamics of our model. Another exciting axis would be the investigation of how our proposed model could be adapted to learn to partition a larger group of swarm into sub-groups as they progress with the search process.

Acknowledgements

This research is supported partially by South African National Research Foundation Grants (No. 112108 and 112142), and South African National Research Foundation Incentive Grant (No. 95687 and 114911), Eskom Tertiary Education Support Programme Grants.

References

[1] Kathleen Mcgill, Stephen Taylor Robot algorithms for localization of multiple emission source. Computing surveys (CSUR) volume 43 issue 3 April 2011

[2] Cui, X., Ragade, R. K., and Elmaghraby, A. S. A collaborative search and engage strategy for multiple mobile agents with local communication in large scale hostile area. In *Proceedings of the International Symposium on Collaborative Technologies and Systems*. 244–249. 2004

[3] Marques, L., Nunes, U., And De Almeida, A. T. Particle swarm-based olfactory guided search. *Auton. Robot. 20*, 277–287. 2006

[4] Gazi, V., Passino, K. Stability analysis of social foraging swarms. *IEEE Trans. Syst.Man Cybernet- Cybernetics, 34*, 1, 539–557. 2004

[5] Passino, K. M. Biomimicry of bacterial foraging for distributed optimization and control. *IEEE Contr.Syst. Mag. 22*, 3, 52–67. 2002.

[6] Krishnanand, K. N. And Ghose, D.. Glowworm swarm optimization for simultaneous capture of multiple local optima of multimodal functions. *Swarm Intell. 3,* 2, 87–124. 2009b

[7] Barlow, G. J., Choong, K. O., And Smith, S. F Evolving cooperative control on sparsely distributed tasks for UAV teams without global communication. In *Proceedings of the Genetic and Evolutionary Computation Conference.* 177–184. 2008

[8] Luke, S., Sullivan, K., Panait, L., And Balan, G. Tunably Decentralized algorithms for cooperative target observation. In *Proceedings of the International Conference of Autonomous Agents and Multiagent Systems.* 911–917. 2005

[9] Murphy, R.R. A decade of rescue robots Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference 2012

[10] Dunbabin, M. ; Marques, L. Robots for Environmental Monitoring: Significant Advancements and Applications Robotics & Automation Magazine, IEEE Volume: 19 , Issue: 1 2012

[11] Micael S. Couceiro, David Portugal, Rui P. Rocha A collective robotic architecture in search and rescue scenarios Proceedings of the 28th Annual ACM Symposium on Applied Computing 2013

[12] D.-C. Dang, T. Friedrich, T. Kotzing, M. Krejca, P. K.Lehre, P. Oliveto, D. Sudholt and A. Sutton, 'Emergenceof diversity and its benefits for crossover in genetic algorithms', in Proc. of PPSN XIV, 2016, pp. 890–900

[13] H. Ishibuchi, H. Masuda, Y. Tanigaki, and Y. Nojima, "Modified Distance Calculation in Generational Distance and Inverted Generational Distance," in Evolutionary Multi-Criterion Optimization. Guimaraes, Portugal: Springer International Publishing, 2015, pp. 110–125

[14] S. Jiang, S. Yang, Y. Wang, X. Liu, Scalarizing functions in decomposition-based multiobjective evolutionary algorithms, IEEE Trans. Evol. Comput. 2017

[15] L. Li, Y. Wang, H. Trautmann, N. Jing, M. Emmerich, "Multiobjective evolutionary algorithms based on target region preferences", Swarm Evol. Comput., vol. 40, pp. 196-215, Jun. 2018.

[16] A. Trivedi, D. Srinivasan, K. Sanyal, and A. Ghosh, ''A survey of multiobjective evolutionary algorithms based on decomposition,'' IEEE Trans. Evol. Comput., vol. 21, no. 3, pp. 440–462, Jun. 2017

[17] M. van Gerven and S. Bohte. Artificial neural networks as models of neural information processing. Frontiers in Computational Neuroscience, 11(114):1–2, 2017.

[18] Chi Man Wong; Chi Man Vong; Pak Kin Wong; Jiuwen Cao, "Kernel-Based Multilayer Extreme Learning Machines for Representation Learning", IEEE Transactions on Neural Networks and Learning Systems;Vol. 29, Iss.3, pp. 757– 762, 2018.