QUALITATIVE ANALYSIS OF USING PARTICLE SWARM OPTIMIZATION FOR MULTI ROBOT AGENTS IN THREE DIMENSIONAL SPACE

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Especially for:

My family that support and motivate me in every aspects of my studies.
My father and my mother whom are like a daylight in my whole life.
My love that is a big motivation for me to continue.

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ABSTRACT

In the field of multi robot systems, algorithms that control communication and movement of multi robot agents has became an interesting arena for researchers recently. A big challenge in this area is to design an effective algorithm which make multi robots to work as a team of robots to perform their task and reach to their goal. In this article we use a Modified version of Particle Swarm Optimization Algorithm that is called MPSA. This algorithm allow us to use a virtual multi robot search to find optima in a three dimensional function space. The presented model has the advantages of being capable to change parameters and number of robots or agents, in order to improve the functionality of the multi agent system. In order to avoid collision with obstacles, we use the "leader follower" technique which can help to change the direction of swarm movement to avoid collision with obstacles while trying to get closer to their target. Simulation results show that with this algorithm, our team of robots can perform a swarm movement to reach the target while avoiding collision among themselves or with the obstacles that may be in the environment.

ABSTRAK

Dalam bidang sistem robot algoritma, pelbagai bahawa komunikasi kawalan dan pergerakan ejen robot berbilang telah menjadi satu arena yang menarik untuk penyelidik baru-baru ini. Satu cabaran yang besar dalam bidang ini adalah untuk mereka bentuk algoritma yang berkesan membuat robot berbilang untuk bekerja sebagai satu pasukan robot untuk menjalankan tugas mereka dan mencapai matlamat mereka. Dalam artikel ini, kita menggunakan versi Diubah Swarm Optimization Algoritma Zarah yang dipanggil MPSA. Algoritma ini membolehkan kita untuk menggunakan carian robot pelbagai maya untuk mencari optima dalam ruang fungsi dimensi tiga. Model yang dibentangkan mempunyai kelebihan yang mampu untuk menukar parameter dan bilangan robot atau ejen, untuk meningkatkan fungsi sistem agen berbilang. Bagi mengelakkan perlanggaran dengan halangan, kita menggunakan "pemimpin pengikut" teknik yang boleh membantu untuk menukar arah pergerakan meluru turun untuk mengelakkan perlanggaran dengan halangan ketika cuba untuk mendapatkan lebih hampir kepada sasaran mereka. Keputusan simulasi menunjukkan bahawa algoritma ini, pasukan kami robot boleh melakukan sebuah gerakan mengeriap untuk mencapai sasaran itu sambil mengelakkan pertembungan sesama sendiri mahupun dengan halangan-halangan yang mungkin berada dalam alam sekitar.

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LIST OF SYMBOLS

Xi,j	-	Position of the particle i in dimension j
Vi,j	-	Velocity of the particle i in dimension j
w	-	Inertia weight
$rand\ ()$	-	Random function
lbest	-	Local best
gbest	-	Global best
$C1$	-	Inertia weight
$C2$	-	Learning factor
$C3$	-	Positive Constant coefficient
$f(x)$	-	Fitness function
$Vmax$	-	Maximum velocity bound
$Vmin$	-	Minimum velocity bound
$Pi(k)$	-	Best position of a particle
$Pg(k)$	-	Best position of all particles
$Wi(k)$	-	Penalty value
$Fi(k)$	-	Fitness function
Ni	-	Set of obstacles
Oj	-	Position of the obstacle j
$Cp1$	-	Penalty parameter
$Cp2$	-	Penalty parameter
rd	-	Threshold radios of the virtual zone for an agent
ro	-	Distance between two agents
m	-	Number of Obstacles
n	-	Number of agents
$\|\| \ \|\|$	-	Symbol of norm

LIST OF ABBREVIATIONS

PSO	-	Particle Swarm Optimization
3_D	-	Three Dimensional
MARS	-	Multiple Agent Robotic System
ODE	-	Ordinary Differential Equation
LTI	-	Linear Time Invariant
MRS	-	Multi Robot System
MPSA	-	Modified Particle Swarm Algorithm
GA	-	Genetic Algorithm
SISO	-	Single Input _ Single Output
MIMO	-	Multi Input _ Multi Output
ANN	-	Artificial Neural Networks
PID	-	Proportional Integral Derivative

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CHAPTER 1

INTRODUCTION

1.1 Overview of PSO

Particle Swarm Optimization (PSO) is a technique used to explore the search space of a given problem to find the settings or parameters required to maximize a particular objective. This technique, first described by J. Kennedy and R. Eberhart (1995), originates from two separate concepts: the idea of swarm intelligence based on the observation of swarming habits by certain kinds of animals (such as birds and fish); and the field of evolutionary computation.

In this proposal first I will mention the significance of MARS , PSO and optimization in general terms, then I will choose a model and algorithm in order to implement the technique in scope of the project and in future the simulations will show the expected results.

Figure 1.1: Swarm of birds

In this scenario, there are two questions that play an important role and caused to attract so many investigations in this field.

First, how may swarm of birds, Figure 1.1, or school of fish, Figure 1.2, execute such a coordinated behaviour in collective tasks? And second, how can we select a good cost function and algorithm and improve them to be capable of implementation in multi robotic systems?

1.2 Background of the Study

The field of robotics has expanded tremendously over last several decades. Swarm Robotics is an emerging area which studies novel approaches to coordinate a large number of relatively simple robots to achieve desired collective behaviours and objectives that would not have been possible for individual robots. Swarm robotics emphasizes scalability, local interaction among agents, and fault tolerance.

Equipping the robots (agents) with the necessary sensors and developing efficient navigation and cooperative search algorithms can lead to improving the performance of the system in terms of more effective exploration/coverage and decreasing the time of search. There have been works on investigating search methods inspired from Particle Swarm Optimization for multi-agent systems. particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position and it is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

Figure 1.2: schools of fish

1.3 Statement of the problem

In robotic field, using a large number of robots which work together cooperatively is very challenging because of so many limitations that may arise in the real environment. When we use unsupervised learning for multi robot agents, some issues such as communication range, transmission power and available energy at their disposal plays important roles in implementation. While trying to use algorithms such as PSO or GA, to have the desired behaviors like swarm of animals in real world, we will find that control of parameters in these scenario is also a big issue that would cause the fast or slow rate of convergence of our algorithm to find an optimum solution for the problem. Robots should cooperate each other as they should perform their own mission as well in the dynamic environment. When the problem space extended to 3_D environment the control of agents becomes harder than before which require a challenging effort to design and model the neighborhoods for the agents to be able to do the swarm movement as the real world.

1.4 Objectives of the research

Objectives of this research are as below:

1. To investigate the performance of utilizing a modified version of Particle Swarm Optimization on large numbers of simulated robots which implement distributed unsupervised learning and to see how the numbers of robots may effect this learning technique.

2. To see how the restrictions in robotic communications with applying our neighborhood structure can influence the learning performance while each robot play the role of a single particle.

3. To apply the MPSA to a cooperative task and explore how the agents or robots can perform the behaviors such as collision avoidance and obstacle avoidance in the problem space and whether they can reach their goal and find the optimum solution in a satisfactory and limited number of iterations of the algorithm.

1.5 Scope of the project

We used a modified version of PSO which called MPSA and applied it to distributed unsupervised robotic learning in team of robots which only have local information about the environment. The efficiency of learning technique for a cooperative task of finding a target which is positioned randomly in the environment, is explored while the numbers of agents or robots also can be varied randomly. The variable neighborhood structure is defined for our model which will be close to the situations of real world. The simulations are done in 3_D space environment and there is no limitation for the area of problem, but there will be a tradeoff between the number of robots or agents and the vastly of the environment which will be shown in the speed of convergence and fast or low rate of finding the optimum solution for our problem.

The model considered for the communication is immune to noise and error free which corresponds to radio transmissions in a noise free environment. There is also no limitation for communication ranges as our robots move in a swarm and are near each other enough to transmit their information without any restriction but the number of agents that are in neighborhood of an agent is different because of the model we use for this which, each robot will have a virtual zone around itself and the number of other robots that are its neighbor and in this zone may change in each iteration of the algorithm.

1.6 Project time-line

MONTHS	JUL	AUG	SEP	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN
Discussion with supervisor												
Studying MARS , PSO , Algorithms & Models												
Setting objectives & scope												
Literature review												
Simulation & programming												
Results & thesis writing												

Table 1.1 : Project Time Table

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