AN ADAPTIVE SWITCHING COOPERATIVE SOURCE SEARCHING AND TRACING ALGORITHMS FOR UNDERWATER ACOUSTIC SOURCE LOCALIZATION

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by

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LIST OF ABBREVIATIONS

ABC	Artificial Bee Colony
AC	Angle Constraint
ACO	Ant Colony Optimization
ADAPSO	Asynchronous Dynamically Adjustable Particle Swarm Optimization
ADC	Analog to Digital Converter
AGV	Autonomous Ground Vehicle
AHRS	Attitude Heading Reference System
A-RPSO	Adaptive Robotic Particle Swarm Optimization
ASV	Autonomous Surface Vehicle
AUV	Autonomous Underwater Vehicle
BFF	Body Fixed Frame
BFO	Bacterial Foraging Optimization
BR	Boundary Reflection
BRW	Biased Random Walk
BW	Brownian Walk
CDF	Cumulative Distribution Function
CG	Center of Gravity
CRW	Correlated Random Walk
DBA	Distributed Bee Algorithm
DC	Direct Current
DKF	Distributed Kalman Filter
DLF	Distributed Smooth Lévy Flight
DOF	Degree of Freedom

dPSO	Distributed Particle Swarm Optimization
ECEF	Earth Centered Earth Fixed
EKF	Extended Kalman Filter
FFT	Fast Fourier Transform
FoV	Frequency of Visiting
GA	Genetic Algorithm
GLRT	Generalized Likelihood Ratio Test
GPS	Global Positioning System
GSO	Glowworm Swarm Optimization
GUI	Graphical User Interface
I2C	Inter-Integrated Circuit
IMU	Inertial Measurement Unit
LBL	Long Baseline
LF	Lévy Flight
LFAPF	Lévy Flight with Artificial Potential Field
LTI	Linear Time Invariant
MANET	Mobile Ad-Hoc Networks
MAS	Multi-agent System
MBFO	Modified Bacterial Foraging Optimization
M-GSO	Modified Glowworm Swarm Optimization
MLE	Maximum Likelihood Estimate
MLPSO	Modified Local Particle Swarm Optimization
MRS	Multi-robotics System
NED	North-East-Down
PAC	Percentage Area Coverage

PDF	Probability Density Function
PEPSO	Physically Embedded Particle Swarm Optimization
PI	Proportional Integral
P-PSO	Probability Particle Swarm Optimization
PSO	Particle Swarm Optimization
PWM	Pulse Width Modulation
RDPSO	Robotic Darwinian Particle Swarm Optimization
ROC	Receiver Operating Curve
RPSO	Robotic Particle Swarm Optimization
RSSI	Received Signal Strength Indicator
RW	Random Walk
SBL	Short Baseline
SD	Source Detection
SDA	Source Detection Algorithm
SI	Swarm Intelligent
SMC	Sliding Mode Controller
SNR	Signal to Noise Ratio
SPI	Serial Peripheral Interface
SPU	Signal Processing Unit
SRS	Swarm-robotics System
ST	Source Tracing
STA	Source Tracing Algorithm
UART	Universal Asynchronous Receiver Transmitter
UAV	Unmanned Aerial Vehicle
USBL	Ultra-short Baseline

LIST OF SYMBOLS

$\hat{\boldsymbol{\alpha}}$	Estimated unknown parameters by MLE
$\bar{\boldsymbol{\upsilon}}$	Average of N_{sam} measured data
$\hat{\boldsymbol{d}}$	Unit vector
$\boldsymbol{a}$	Accelerometer measurement vector
$\boldsymbol{A}$	State space system matrix
A_{in}	Cross-sectional area of water pump inlet
A_{out}	Cross-sectional area of water pump outlet
a_x	Linear acceleration in surge direction
a_y	Linear acceleration in sway direction
b	Distance between left and right thrusters
$\boldsymbol{B}$	State space input matrix
$\boldsymbol{B}_{\tau}$	Thruster configuration matrix
$\boldsymbol{C}$	Coriolis-centripetal matrix
c_1	Cognitive acceleration coefficient
c_2	Social acceleration coefficient
$C_i(t)$	Neighboring robots of robot i within critical communication distance
c_{ini}	Initial value of acceleration coefficient
c_l	Location parameter of a Lévy-stable distribution
C_n	Normalization constant of a power law distribution
$\boldsymbol{D}$	Damping matrix
d_{com}	Desired communication distance
d_{ij}	Distance between robot i and robot j
d_{rs}	Distance between robot and source

E	Edge of undirected graph
e_{ij}	Edge between robot *i* and robot *j*
f	Robot fitness
F_a	Attraction force
f_a	Frequency of acoustic source
F_{CDF}	CDF of the desired distribution transformation
$F_{col,max}$	Maximum collision avoidance force
$F_{col,tot}$	Total collision avoidance force
F_i	Total interaction force experience by robot *i*
F_{ij}	Interaction force between robot *i* and robot *j*
F_{max}	Maximum magnitude of interaction force
f_{max}	Maximum frequency
$f_{Nyquist}$	Nyquist frequency
F_r	Repulsive force
f_s	Sampling frequency
F_{TL}	Left thruster force
F_{TR}	Right thruster force
G	Undirected graph
$\boldsymbol{g}$	Buoyancy/gravitational matrix
gBest	Global best position
g_i	Convergence speed factor for robot *i*
H_0	Null hypothesis
H_1	Alternative hypothesis
h_i	Evolutionary speed factor for robot *i*
h_s	Depth of underwater acoustic source

h_w	Submerged depth of the ASV hull
I_0	Initial intensity value of source
$I_{f,max}$	Final maximum intensity value
I_{max}	Maximum source intensity
$I_n(t)$	Source intensity measured robot n at time t
I_{TH}	Intensity threshold
J_z	Moment of inertia
k	Iteration or step number
K_{cr}	Tuning parameter for collision avoidance
K_i	Integral controller of PSI controller
K_p	Proportional gain of PI controller
k_{run}	Total number of runs
k_{stp}	Total number of steps
L	Generalized likelihood ratio test
l_{avg}	Average step length
l_k	Levy flight step length at k step
l_{min}	Levy flight minimum step length
m	Mass of ASV
$\boldsymbol{m}$	Magnetometer measurement vector
$\boldsymbol{M}$	System inertia matrix
N	Number of robots in the swarm
n	Robot index
$\boldsymbol{N}$	Normal vector to the search space boundary
n_A	Search space size multiplier
N_c	Number of converges robot

N_{exp}	Number of experiment
NG_{tot}	Total number grid or search space division
NG_{vis}	Number of visited grids
N_{PD}	Number of successive probability of detection
$N_{s,i}$	Number of neighboring robots for robot i
N_{sam}	Number of samples
$\bar{\boldsymbol{p}}$	Average robot position
$P(\cdot)$	Probability of distribution of parameter $(\cdot)$
$\boldsymbol{p}(k)$	Waypoint at step k
$\boldsymbol{p}^*$	Global optimum position
P_a	Acoustic pressure
pBest	Personal best position
P_D	Probability of detection
P_{DTH}	Probability of detection threshold
$\boldsymbol{p_e}$	Position in ECEF reference frame
P_{FA}	Probability of false alarm
$\boldsymbol{p_g}$	Geodetic position vector
p_h	Poles of SMC controller
P_{H0}	Probability distribution under null hypothesis
P_{H1}	Probability distribution under alternative hypothesis
$\boldsymbol{p_n}$	Robot position in NED reference frame
$\boldsymbol{p_n}(t)$	Position vector of robot n at time t
P_{opt}	Set of optimal parameters
$\boldsymbol{p_s}$	Source position
Q	A stable distribution constant

$\boldsymbol{q}$	Quaternion
$\boldsymbol{q_i}$	ADAPSO position vector for network connectivity maintenance
r	Yaw rate or yaw angular velocity
$\Re$	Space vector
$\boldsymbol{R}(\cdot)$	Rotation matrix in term of $(\cdot)$ angle
r_a	Radius of acceptance
R_{ASV}	Radius of ASV
r_{att}	Attraction radius
r_c	Radius communication
r_{con}	Convergence radius
r_d	Radius of detection
r_{ini}	Initialization radius
R_n	Robot identity tag where n=1,2,…,N
r_{neu}	Neutral radius
r_{rep}	Repulsive radius
SC_c	Searching counter
s_i	Aggregation degree
t	Time
T	Test statistics
t_{max}	Maximum allowable searching time
T_s	Sampling time
T_{SD}	Total source detection time
T_{ST}	Total source tracing time
t_T	Total time to complete previous operation
T_{tot}	Total time

U	Uniformly distributed random number
u	Velocity in surge direction
$\boldsymbol{u}$	Control system input vector
U_b	Speed over the ground in body frame
u_{max}	Maximum speed
U_n	Speed over the ground in NED frame
U_v	Speed over the ground
V	Vertices of undirected graph
v	Velocity in sway direction
v_{in}	Inlet velocity of water pump
V_l	Volume
V_{max}	ADAPSO maximum speed limit
$\bar{V}_{noise}$	Average noise power
v_{out}	Outlet velocity of water pump
$\bar{V}_{signal}$	Average signal power
w	Gaussian white noise
$\boldsymbol{W}$	Matrix of environmental disturbances
$\boldsymbol{X}$	Search space
$\boldsymbol{x}$	State vector
$\mathrm{X}_{\mathrm{i,exp}}$	Experimental data at *i* repetition
$\mathrm{X}_{\mathrm{i,sim}}$	Simulated data at *i* repetition
x_{max}	Maximum of *x*-position of a search space
x_{min}	Minimum of *x*-position of a search space
x_n	x-position in NED frame
y_{max}	Maximum of *y*-position of a search space

y_{min}	Minimum of *y*-position of a search space
y_n	y-position in NED frame
α	ADAPSO inertia weight increment multiplier
β	ADAPSO inertia weight decrement multiplier
B_{ang}	Side-slip angle
γ	Detection threshold from GLRT
δ	Damping ratio of PI controller
$\Delta(\cdot)$	Change of variable $(\cdot)$
ε	Desired false alarm rate
$\boldsymbol{\eta}$	Position-orientation matrix
η_{ch}	Switching gain of SMC heading controller
θ	Turning angle
Θ	Roll angle
ϑ	Pitch angle
θ_{min}	Turning angle limit
κ	PSO constriction factor
Λ	Percent fitness difference between converged robots
λ_{att}	GPS attitude measurement
λ_{lat}	GPS latitude measurement
λ_{lon}	GPS longitude measurement
μ	Power law exponent or scaling parameter of Lévy flight
ξ_0	Average noise
ξ_1	Average signal plus noise
ϖ	Angular speed
ρ	Water density

ς	Shape control parameters of a stable distribution
σ^2	Variance
$\boldsymbol{\tau}$	Generalized force
τ_r	Thrust in sway direction
τ_u	Thrust in surge direction
$\boldsymbol{\upsilon}$	Measured signal intensity value
Φ	Boundary layer thickness of a sliding mode controller
φ_k	Relative turning angle at step k
ϕ_k	Absolute turning angle at step k
ϕ_{new}	New absolute turning angle
χ	Course angle measured by GPS
ψ	Yaw angle in NED frame
ω	Inertia weight value of ADAPSO or PSO
ω_{ini}	Initial inertia weight value of ADAPSO
ω_n	Natural frequency of PI controller

ALGORITMA PENCARIAN DAN PENJEJAK SUMBER BESEPADU BOLEH UBAH UNTUK LOKALISASI SUMBER BUNYI BAWAH AIR

ABSTRAK

Robotik kawanan adalah satu bentuk kajian tentang bagaimana untuk mengatur sejumlah robot yang agak banyak tetapi ringkas untuk mendapatkan kaedah penyelesaian yang tahan lasak, mempunyai kebolehlenturan dan berskala. Mencari sumber yang mempunyai corak pengedaran ruang yang rumit adalah salah satu tugas yang boleh dilakukan oleh robotik kawanan. Dalam tugasan ini, terdapat dua kemungkinan yang boleh berlaku iaitu sumber dapat dikesan dan sumber tidak dapat dikesan. Dalam kajian ini, penyelesaian kepada dua kemungkinan tersebut diterokai melalui strategi penukaran algoritma secara penyesuaian. Pertama, untuk pengesanan sumber, Algoritma Pengesanan Sumber (SDA) yang dikenali sebagai Agihan Penerbangan Lévy (DLF) diperkenalkan. Untuk meningkatkan keupayaan penerokaan pada peringkat individu ejen, had sudut peralihan dan pantulan di sempadan kawasan carian diperkenalkan. Untuk mengoptimumkan penerokaan ruang carian dan untuk mengekalkan hubungan komunikasi antara kawanan robot, algoritma penyebaran berdasarkan daya tarikan dan daya penolakan dicadangkan. Kedua, untuk menjejaki lokasi sumber, Algoritma Penjejakan Sumber (STA) yang dikenali sebagai kaedah Pengoptimuman Kelompok Zarah Boleh Ubah Tidak Serentak (ADAPSO) dicadangkan. Untuk meningkatkan keupayaan menjejak bagi mengelakkan robot terperangkap ke dalam lokasi optima lokal dan untuk meminimumkan kebarangkalian terlajak sasaran, pekali inersia dan pekali pecutan untuk ADAPSO dikemas kini secara penyesuaian dan tidak serentak. Sebagai

tambahan, persamaan kedudukan algoritma ADAPSO diubahsuai untuk memastikan kesinambungan rangkaian komunikasi. Untuk penukaran antara algoritma, algoritma penukaran secara adaptif melalui keadah Ujian Nisbah Kemungkinan Umum (GLRT) diperkenalkan. Untuk membuktikan keberkesanan kaedah yang dicadangkan, satu kajian kes mengenai pencarian sumber akustik bawah air menggunakan Kenderaan Autonomi Permukaan Air (ASV) dilakukan. Berdasarkan model ASV yang dibangunkan, setiap algoritma dinilai dan ditanda aras berdasarkan beberapa kaedah sedia ada melalui kajian simulasi. Hasil simulasi membuktikan bahawa prestasi algoritma DLF yang dicadangkan mencapai peningkatan peratusan penerokaan ruang dan penurunan masa menjejaki berbanding algoritma yang ditanda aras. Algoritma ADAPSO pula mencapai peratusan peningkatan kejayaan menjejak dan penurunan kadar masa yang diambil untuk menjejaki sumber berbanding algoritma yang ditanda aras. Akhir sekali, keberkesanan strategi pencarian sumber yang dicadangkan dibuktikan melalui penyelesaian masalah tersetempat sumber akustik bawah air melalui kaedah simulasi dan ujikaji di mana ketepatan anggaran purata kedudukan sumber bunyi yang dicapai adalah 0.4 m untuk hasil simulasi dan 4.2 m untuk hasil eksperimen.

AN ADAPTIVE SWITCHING COOPERATIVE SOURCE SEARCHING AND TRACING ALGORITHMS FOR UNDERWATER ACOUSTIC SOURCE LOCALIZATION

ABSTRACT

Swarm robotics is a study of how to organize a relatively large number of simple robots to achieve a robust, flexible and scalable solution for a given task. Searching a source with a complex spatial distribution pattern is one of the possible swarm robotics tasks. In a source searching task, two possible scenarios can occur: source detected and source not detected. In this study, a complete solution to the two scenarios through an adaptive algorithm switching strategy is explored. Firstly, to detect the source, a Source Detection Algorithm (SDA) known as a Distributed Lévy Flight (DLF) is proposed. To improve exploration performance of the individual agent, a turning angle limit and boundary reflection is introduced in DLF. In order to optimize search space exploration and to maintain inter-robot communication connectivity at swarm level, a dispersion algorithm based on attraction and repulsion force is proposed. Secondly, to trace the source to its approximate location, a Source Tracing Algorithm (STA) known as an Asynchronous Dynamically Adjustable Particle Swarm Optimization (ADAPSO) is suggested. The ADAPSO parameters are adaptively and asynchronously adjusted based on feedback informations to improve convergence speed, to avoid robot trapped into local optima and to minimize target overshooting. In addition, the ADAPSO position update equation is modified to anticipate position adjustment to ensure communication connectivity. To adaptively switches between the two algorithms, an adaptive switching algorithm based on a

Generalized Likelihood Ratio Test (GLRT) is proposed. To demonstrate the algorithm switching principle, underwater acoustic source localization using a swarm of Autonomous Surface Vehicles (ASVs) is considered. By considering the ASVs as swarm robotics testing platforms, each algorithm is evaluated and benchmarked against several existing algorithms through simulation studies. The obtained results show that the performance of the DLF for source detection outperformed other benchmark algorithms in term of search space exploration capability and the time taken to detect the source. The ADAPSO for source tracing achieved better tracing performance with better success rate and reduced the time taken to trace the source to its approximate location compared to the benchmark algorithms. Finally, the feasibility of the proposed algorithms for underwater acoustic source localization is confirmed through simulation and experimentation where the achieved average accuracy of source position estimation is 0.4 m and 4.2 m, respectively.

CHAPTER ONE

INTRODUCTION

1.1 Background and Motivation

Robots have been used for various applications over the past few decades. Since the beginning of the robotics era, several types of robotic systems have been developed to accommodate modern-day tasks which are complex and challenging to solve. In early age of robotic system development, a single robotic system has been developed from a complex connection of electromechanical pieces which is complicated to design, situated in place (i.e. immobile), expensive to fabricate and possesses limited capability and autonomy. However, rapid evolution of robotics research supported by advancement of sensors, actuators, communications and data processing technology, the functionalities, autonomies and capabilities of the robotic systems has been significantly improved. As a result, a multi-robotics system (MRS) which consists of autonomous robots has been introduced in mid 90s to perform tasks that are not feasible to a single-robotic system (Veloso and Nardi, 2006).

Applications of MRS cover a wide range of tasks such as tasks that are unreachable and dangerous to human operator, tasks that involve wide area coverage, and operations in a complex and unstructured environment. However, many of these applications not only require multiple robots to work autonomously and cooperatively but they also need to be robust, flexible and scalable in order to adapt to the change of the preset conditions of a given task and workspace. To fulfill the aforementioned requirements of robotic task, swarm robotics system (SRS) has been later introduced and currently, swarm robotics has become one of the most active research areas in the field of robotics. Technically, swarm robotic has been defined as (Şahin, 2005):

> "*the study of how large numbers of relatively simple, physically embodied agents can be designed such that a desired collective behavior emerges from the local interactions among agents and between the agents and the environment*."

The concept of swarm robotics is closely related to the principle of swarm intelligence (SI) and multi agents system (MAS) in which both are inspired mostly by the social behaviors of insects, microorganisms or animals in nature. Some examples include cooperative and social behavior of ants, birds, fish and bees performing their routine activities or task in the absence of a group leader as portrayed in examples shown in Figure 1.1. Some examples of the collective behavior can be observed in nature include termites building a giant nest, red ants searching for foods, a migration of geese, honey bees foraging, a flock of fish avoiding predators, etc. These examples share a common characteristic where the extraordinary behavior is shaped by simple local interactions among the individuals.

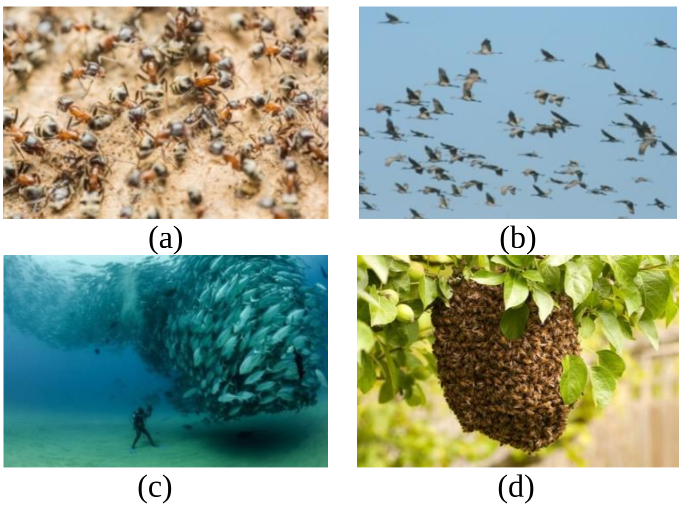

Figure 1.1: Examples of collective task in nature (a) Ants (b) Birds (c) Fish (d) Bees

In the perspective of swarm, each member of the swarm is not capable of performing a meaningful group task on their own due to limited capability. However, a variation of complex tasks can be easily performed through collective behavior as a result of local interaction between member of the swarm and its nearest neighbors. Thus, the cooperative behavior has become one of the fundamental requirements in swarm robotic applications. As a result of cooperative behavior based on local interaction, swarm robotic has three distinctive advantages compared to other types of robotic systems, namely, flexibility, scalability and robustness. According to (Şahin, 2005), these characteristics can be defined as:

- *Flexibility* – The ability of the swarm robot to withstand the change of environments and tasks by adjusting their cooperative strategies and generating modularized solutions, respectively.
- *Scalability* – The capability of the swarm to perform well with different group size to accommodate different sizes of workspace and complexity of the assigned group task.
- *Robustness* – The capability of the swarm to cope with losses of one or more robots from the group without deteriorating the given task through a decentralize coordination and local interaction.

These characteristics allow swarm robots to perform a relatively complex task by using a relatively simple cooperative algorithm embedded into a group of a physically simple robotic platform. However, despite of huge efforts on research and development have been made to optimize swarm robotic to its full potentials, it is considered as a relatively new and immature robotic technology. From the perspective of current stage of swarm robotic research and development, there are none (i.e. if not a few) commercial applications can be found have adapted SRS for solving real world problems (Tan and Zheng, 2013). It dictates that the SRS research field is widely opened to be explored and studied stretching from fundamental idea to concept development towards real world implementations and testing. Thus, this factor becomes one of the key motivations that motivate this research work.

Swarm robotic has enormous potential for real world applications and tasks especially the one that is not possible or inefficient to be performed using a single robotic system. In general, different types of task that suit SRS can be classified into several categories such as task that is dangerous to human, task that requires area coverage, task that demands number of robots to be scaled up/down and task that requires redundancy (Şahin, 2005, Tan and Zheng, 2013). Source searching or source seeking is one of the tasks that falls within the classification. In real world scenarios, source searching and localization is an important task in many applications such as in a search and rescue operation, environmental monitoring, detection of chemical leakage, mine countermeasures, searching for a flight recorder (black box) and scientific studies. An example application of source searching task using swarming robots in search and rescue operation is illustrated in Figure 1.2.

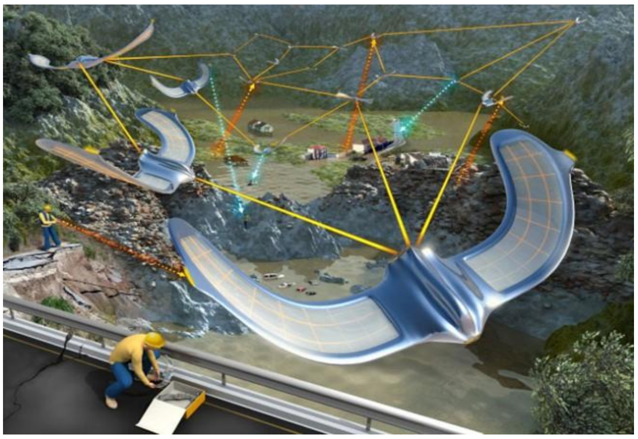

Figure 1.2: Cooperative searching task in search and rescue operation using swarm robots (Hauert et al., 2013)

For a source searching and localization task, swarm robotic offers several advantages compared to other types of robotic systems such as it reduces searching time, provides large area coverage and not easily trapped into a local optima (Li et al., 2008a). Swarm robotics is proven to be reliable and practical for source searching task, especially if the sources exhibit a complex or a non-smooth spatial pattern of distribution such as acoustic, magnetic, radioactive, light, heat, biology and chemical odor in which source's intensity strength is influenced by the characteristics of the surrounding environment and the transferring medium (Navarro and Matia, 2013). Searching these types of sources is a challenging task because there is no guarantee that the source is detectable throughout the entire search space to assist a direct searching process (Jatmiko et al., 2011). Thus, considering this issue, a complete and reliable source searching algorithm should be developed considering the inconsistency of source signal detection.

Depending on type of operation on demands, the source searching task can take place in different types of search space. Despite of many potential applications, source searching in an underwater environment has not been extensively studied. In underwater environments, one of the source searching tasks is to search and localize an unknown location of an acoustic source in a noisy underwater environment (Paull et al., 2014). The real world examples include searching for a flight black box after airplane crash and recovery of a failure underwater vehicle in a remote ocean environment. In these examples, the interested source is an acoustic signal (i.e. specifically a ping signal). Acoustic signal exhibits a complex spatial pattern distribution characteristic where its intensity measurement is strongly influenced by noises from the surrounding environment. In addition, a large search space makes it even harder to detect the signal if only a single searching platform is used to locate the source. Searching using a single platform becomes inefficient because of a large and unpredictable search space involves. Thus, swarm robotics which offers a simple and a low cost solution (i.e. due to simple robotic platform and algorithm as per swarm robotic definition) can be employed to autonomously search and locate the underwater acoustic source within the unknown environment.

In order to implement a source searching algorithm in a real environment, a suitable swarm robotic platform must be considered. Currently, for an on ground source searching and localization task, mobile robots have been widely used due to high maneuverability, easy to control, possesses reliable communication and positioning systems and the platform is commercially available. For underwater source searching task, two types of robotic platform can be considered: autonomous surface vehicle (ASV) or autonomous underwater vehicle (AUV). Nevertheless, ASV has advantages of simpler communication and positioning, easier to control and its development cost is lower compared to AUV. However, unlike mobile robot, a conventional type of ASV has disadvantages of relatively low maneuverability due to poor turning capability especially in a bounded workspace and thus, not applicable when the source searching algorithm requires fast turning while transitioning from one direction to another. Thus, these issues motivate the need of designing a new ASV platform specifically for underwater source searching and localization.

1.2 Problem Statement

Automatic source searching using autonomous robot has long been studied to replace or to assist human in solving many real life problems in order to optimize searching time and to handle hazardous task (Zohar et al., 2009). Source searching using a single robotic system has low accuracy, slow convergence speed and lack of robustness (Akat et al., 2010, Sànchez et al., 2018). In contrast, source searching using multiple robots is a relatively new research field and has not yet been comprehensively studied (Couceiro et al., 2014b, Cao et al., 2015). Source searching using multiple robots has better performance in term of searching time, robustness and accuracy compared to a single robotic system (Tang and Eberhard, 2013). Additionally, source searching using multiple robots has better decision making due to the capability of providing multiple and simultaneous sensors reading which is not applicable in a single robotic system. Swarm robotic enhances these capabilities further by providing a flexible, scalable and robust solution to the problem through a cooperative algorithm (Chung et al., 2018, Sànchez et al., 2018).

In a real source searching problem, there are three possible scenarios can occur due to robot limited sensing range and intensity decaying property of the source. Firstly, there is a possibility that the source is not detected as soon as robots are deployed into the search space. In this scenario, robots must rely on an algorithm which is independent of source intensity to optimize search space exploration in order to optimize detection time. Secondly, there is possibility that the intensity of the source is directly detected once robots are deployed into the search space. In this case, an algorithm which exploits source intensity measurement must be used to optimize convergence speed and accuracy of convergence. In the third scenario, robots do not detect the source once they are deployed but the source may become detected after robots explore the search space and vice versa. In this case, independent algorithms for both detectable and undetectable source signal must be considered. As a result, a complete and optimal source searching algorithm must be able to work in both situations where source signal is detected and source signal is not detected. Currently, this issue has not been thoroughly studied where in most studies it assumed that source signal is always detected or a nonoptimal random movement is considered when source is not detected (Melo et al., 2018, Kumar et al., 2017, Husni et al., 2017). Thus, the problem statement is stated as follow:

In a real source searching task, source signal is not always detected throughout the searching period and searching space. Thus, a source searching algorithm without considering the possibilities of source signal being detected and source signal not being detected may cause the overall source searching failure.

In order to switches between the two independent algorithms (i.e. algorithm when source is detected and algorithm when source is not detected), a switching strategy is needed where robot should be able to adaptively switches between the two algorithms depending on the measured source signal intensity. Currently, a switching algorithm uses a direct threshold setting where robot switches from one algorithm to another when the measured source signal intensity exceeds or falls below a specific threshold value (Nurzaman et al., 2010, W. Jatmiko, 2016, Khan et al., 2016). However, this approach does not consider the effect of background noise level and source signal strength which may causes switching error and the confident level of detection cannot be monitored. Moreover, the corresponding threshold must be determined manually and an appropriate intensity threshold is difficult to determine. Additionally, in order to implement source searching algorithm for underwater acoustic source localization, ASV which offers a simple and reliable communication, positioning and control can be used. However, a conventional ASV platform for swarm robotics has low maneuverability due to large turning radius as a result of a large length to breadth ratio of the hull (Ghosh, 2016). Thus, a conventional type of ASV is not reliable for implementing a source searching algorithm which requires fast turning and involves relatively small step length of movement.

1.3 Research Objectives

The main objective of this study is to develop an optimal source searching algorithm by considering underwater acoustic source localization as a case study. The sub-objectives of the research are:

i. To develop an optimal source searching algorithm considering detectable and undetectable source signal
ii. To develop an adaptive switching algorithm considering source signal strength and noise level
iii. To develop a reliable swarm robotics platform for underwater acoustic source localization

1.4 Research Scopes

In this study, some limitations have been imposed to simplify the study process. The scopes of this research are:

i. The source is assumed to be a static underwater pinger located in a two dimensional search space and the noises that affect the intensity measurement are assumed to be Gaussian white noise to closely resemble distribution characteristic of actual noise measured by sensor.
ii. The testing environment is assumed to be free from the obstacles and thus, obstacle avoidance algorithm and the possibilities of collision with obstacles are not considered.
iii. Some performance evaluations are restricted to simulation studies only such as variation number of robots and variation of search space size due to limited number of prototypes have been developed and search space is limited to a single size swimming pool, respectively.

iv. Experiments are performed in a controlled environment where the influences of the environmental disturbances such as wind, wave and current have been ignored due to inaccessible information. Thus, all experiments are conducted in a calm Olympic size swimming pool.

1.5 Thesis Outline

This thesis consists of six chapters and it is organized as follows: Chapter 1 presents the introduction of the dissertation and discussed the background and motivation of the study. Problem statements, significance of the problem, research objectives, research scopes, thesis outline are also presented. In Chapter 2, an overview of swarm robotics, state of the art and comparison of swarm robotic source searching methods are discussed in detail. This chapter also reviews briefly about the transformation of autonomous robot for swarm robotic application specifically ASV. Finally, a brief overview of underwater acoustic source localization is also conveyed. In Chapter 3, a complete development of the localization strategy is discussed which include the source localization problem formulation, source detection algorithm development, source tracing algorithm development, adaptive switching algorithm, communication framework and initialization and termination conditions. In Chapter 4, ASV prototype development, ASV modeling and parameters identification, ASV controller design and algorithm implementation are discussed in details. The simulation design and experimental design are also discussed. In Chapter 5, the discussions of the research findings related to the proposed localization strategies are presented and the performance comparison against several benchmark algorithms is also discussed. Finally, a brief summary of the research findings, the overall contributions of the study and the recommendations are highlighted in Chapter 6.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this chapter, a review related to this research work is presented. Firstly, a brief overview of the swarm robotics system which includes its characteristic, communication topology and control architecture classification is discussed. Secondly, the swarm robotics source searching problem classification is briefly highlighted and the corresponding source searching methods are comprehensively reviewed. Then, a comparison study and gap analysis of the swarm robotics source searching methods is presented. Thirdly, a brief review of autonomous surface vehicle design in the perspective of swarm robotic platform is also discussed. Finally, a brief discussion on the different types of underwater acoustic source localization methods and its limitations is presented.

2.2 Swarm Robotic Overview

In order to study swarm robotic for a specific task, it is necessary to provide a general overview of the fundamental concept of swarm robotic. In this section, the basic characteristics, communication topology and control architecture of the swarm robotic system (SRS) are briefly discussed. In general, a swarm robotic system is uniquely characterized by five characteristics that differentiate the system from other types of robotic system. The characteristics of swarm robotics and some important remarks related to the corresponding characteristics are summarized in Table 2.1. In general, swarm robot communication architecture can be classified into two types: explicit (i.e. direct) and implicit (i.e. indirect).

Table 2.1: Characteristic of swarm robots

Characteristics	Remarks
Autonomous	• Possess sensors and actuators to navigate and perform task autonomously (Brambilla et al., 2013) • Able to avoid collision with obstacles and other robots (Tan and Zheng, 2013)
Large Number	• Number of robots is acceptable as long it is permitted by the control rules (Navarro and Matia, 2013) • Examples:14 robots (Couceiro et al., 2014b), 5 robots (Li et al., 2014), 4 robots (Pugh and Martinoli, 2006), 3 robots (Hereford and Siebold, 2010, Ma'sum et al., 2013) • Depends on a specific task (Bratton and Kennedy, 2007, Boubou and Tagawa, 2011)
Limited Capabilities	• Limited sensing, communication and processing power • Each robot should not be assigned with a specific role (Tan and Zheng, 2013)
Local Sensing & Communication	• Robot can only sense and communicate with its nearest neighboring robots (i.e. robot within limited communication range) (Tan and Zheng, 2013)
Homogenous Robots	• Homogenous in term of both physical structure and capability (Dorigo et al., 2013, Patil et al., 2016) • It is acceptable as long as number of the non-homogenous robots are relatively smaller compared to homogenous robots (Navarro and Matia, 2013)

In implicit communication or known as *stigmergic*, communication is established through-the-world interactions (Couceiro et al., 2014b, Aleksandar and Diego, 2007). The characteristics of the *pheromone* based communication include the message is conveyed through the environment, the conveyed message is not directed or specified to a specific recipient and the deposited messages are localized within the space (Paull et al., 2014). Currently, implicit communication is realized in swarm robotic by using visual sensor, stereo vision wireless data (Gray, 2009, Zetterstrom, 2007) or beacons to represent virtual pheromone (Meng et al., 2007). Implicit communication is scalable and reliable for when explicit communication link cannot be established. However, this type of communication disappeared over time and eventually difficult to establish and not practical for tasks that require fast and rapid data sharing such as searching, localization and mapping.

In explicit communication, information exchange takes place through a wireless communication such as Wi-Fi, Bluetooth, acoustic, etc. (Kernbach et al., 2013). The advantages of explicit communication include it is well established, it can guarantee accuracy and consistency of the information exchange among the robots and it is easier to implement compared to the stigmergic communication. However, as the number of the robots in the network increase, burden on the communication network also increases. In swarm robotic, this problem is solved by using local communication topology to minimize data congestion (Senanayake et al., 2016). Typically, graph-theory is used to model communication among the robots (Navarro and Matia, 2013) and one of the main concerns is to maintain mobile ad-hoc network (MANET) in a swarm or multiple swarms (Couceiro et al., 2014b).

In general, there are two types of control architecture commonly implemented in SRS, namely centralized and distributed architectures. In a centralized control, task is implemented based on a central command where a host monitors and gives necessary command during the overall control process. The main advantages of a centralized architecture includes it is easy to monitor and robot behavior can easily be planned before execution (Barca and Sekercioglu, 2013). However, this type of control architecture is computationally expensive for large number of robots (Şahin, 2005), lack of robustness (Parker, 2008) and causes faster energy depletion due to excessive processing (Barca and Sekercioglu, 2013). However, many research works found in literature rely on distributed control architecture. The distributed control allows simplification of the algorithm implementation and parallelism where control burden is distributed to all agents and complexity of the control is not associated with a specific number of robots (Barca and Sekercioglu, 2013). It also reduced the possibility of the entire system failures and promotes scalability since there is no single central processor is responsible to command the overall operation. However, the distributed control architecture does not allow system to be developed based on global knowledge since there is no central informations are collected during the process.

2.3 Swarm Robotic Source Searching

Source searching problems have been studied extensively in the past using a single robotic system but it possesses many limitations such as slow convergence, attempts to fail, inflexible, not scalable and incurs high cost of operation (Wang et al., 2014, Das Sharma et al., 2014, Pugh and Martinoli, 2007, Jatmiko et al., 2011). On the other hand, scalability, flexibility and robustness characteristics of the swarm robotic make it reliable for source searching task and it has been proven to be efficient compared to a single robotic system (Senanayake et al., 2016, Hayes et al., 2002). Source searching task is important in many real world applications such as in a search and rescue operation, detection of harmful gases and chemical leakage (Ferri et al., 2009). To accommodate complexity of the searching task, the algorithm must be designed to be distributed, computationally simple, scalable and must allow for a continuous movement of the robots (Hereford and Siebold, 2010). The swarm robotic source searching task has been studied from different perspectives of the source searching problem. Moreover, this problem has been solved using different methods and strategies which include swarm intelligence, stochastic and systematic approaches. Details are reviewed in the following subsections.

2.3.1 Classification of Source Searching Problems

In general, there are many research topics related to swarm robotics have been studied and explored by swarm robotics research community where some related topics are listed in Figure 2.1. However, for the purpose of this research work, a specific topic which is swarm robotic collective source searching and localization is explored (indicated by the *). Source searching (or source seeking) tasks have been studied using many types of robotic systems which include single robotic system, multi robotics system and swarm robotics system. In a general classification, swarm robotics source and target searching problems can be classified into several major classes of searching problems. This classification can be made based on number of the targets to be searched, type of the targets, mobility of the targets and trackers and complexity of the environment. The classifications of the robotic source or target searching problems based on these criteria are summarized in Table 2.2. The solution to these source searching problems can be categorized based on three major approaches: swarm intelligence (SI) based searching, random based searching and systematic (i.e. deterministic) based searching.

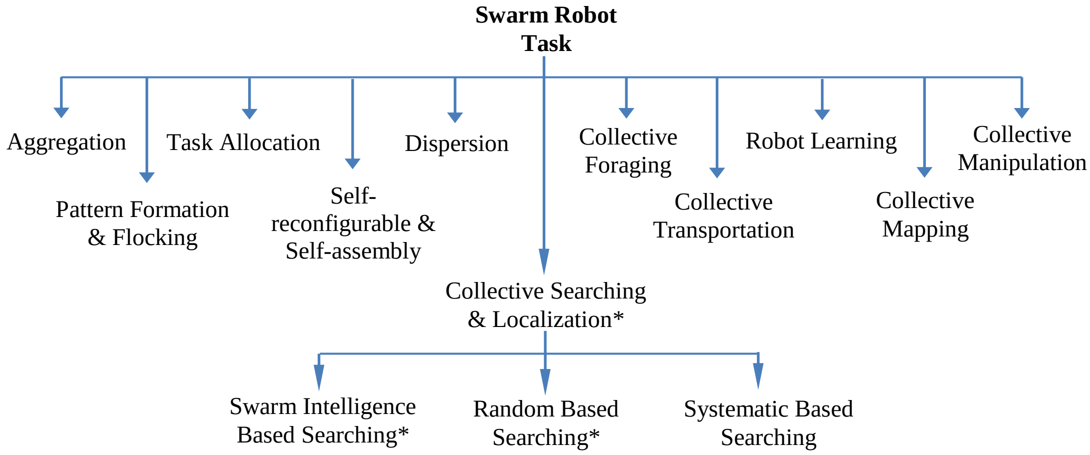

Figure 2.1: Swarm robotics task classification

Table 2.2: Classification of swarm robotic target search problem and related works

Search Classification	**Sub Classification**	**Main Task**	**Example**	**Related Work**
Number of Target	Single target	Optimize searching time	Gas, chemical	Zou et al. (2015), Arvin et al. (2018)
	Multiple targets	Optimize number of target found within a specified searching time	Sound	Sakurama and Nishida (2016), Kumar et al. (2017)
Types of Target or Source	Uniform distribution source	Optimize searching time based on gradient or non-gradient approach	Light	Jada et al. (2017)
			Sound	Shaukat et al. (2013)
			Electromagnetic	Basiri et al. (2014)
	Non-uniform distribution source	Source searching considering environmental dynamic and measurement uncertainty	Chemical plume	Li et al. (2008a), Jatmiko et al. (2011), Braga et al. (2017)
			Gas odor	W. Jatmiko (2016)
Target Mobility	Mobile Target	Search and track source considering mobility of the source	Marine animals	Wang and Gu (2012)
	Static Target	Optimize searching time	Black box	Jada et al. (2017), Husni et al. (2017)
Tracker Mobility	Mobile Tracker	To cooperatively explore the environment and searching for the target or source of interest	A swarm of mobile robot	Wang and Gu (2012), Sakurama and Nishida (2016)
	Static Tracker	Served as active beacons either for indirect communication or positioning reference	Implicit communication	Hollinger et al. (2009), Russell et al. (2015)
Environment Complexity	Open	Studies of dispersion and exploration method for covering large area	Ocean, lakes, underwater	Suarez and Murphy (2011), Sutantyo et al. (2013)
	Unstructured	Search planning including navigation and communication during searching	Under the ruins of a collapsed building	Songdong and Jianchao (2008), Hereford and Siebold (2010), Dadgar et al. (2016)

2.3.2 Swarm Intelligence Search Methods

Animals, insects and microorganisms use various movement strategies to optimally search for food. They perform this task through a direct or an indirect interaction among the members of the group (Tan and Zheng, 2013). Inspired by the intelligence and collective behavior of the socialize animals, swarm intelligence (SI) has been introduced to implant artificial intelligence behaviors to a multi-agent system (Blum and Li, 2008). The concept of SI has been widely adopted to solve many optimization problems. A population-based optimization algorithm based on SI is known as a metaheuristic search method in the field of computer science and mathematical optimization (Ting et al., 2015). In robotics, there are two possible ways to perform source searching task: by sweeping the entire area (i.e. exhaustive search) or by adopting simple yet efficient biological inspired rules (Couceiro et al., 2014b). However, the latter approach is well-suited with the working principle and nature of swarm robotic system (Şahin, 2005, Krishnanand and Ghose, 2017).

The main purpose of the biological inspiration in source searching task is mainly to expedite the searching and exploration process and to obtain a better result (Pina-Garcia et al., 2016). SI based optimization problem and swarm robotics source searching task share a similar problem solving methodology where both are technically searching for the best or near-optimal solution within a specified search space by using multiple agents (Senanayake et al., 2016). In swarm robotics research, SI based optimization algorithms are commonly adopted for source localization and source searching task because the task itself is distributed in time and space (Parker, 2008). Since most of the SI based optimization algorithms are simple yet effective in providing optimal solution, many source searching algorithms are developed based on SI approaches compared to other exhaustive search strategy (Khaldi and Cherif, 2015). Thus, to discuss further, a critical review of some selected SI based optimization algorithms and related works in swarm robotics source searching task are presented in the next subsections.

2.3.2(a) Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) was initially developed to model flocking behavior of birds and fish (Kennedy and Eberhart, 1995). The basic concept of PSO is to allow a number of particles (i.e. the possible solutions) flown through a solution space where these particles are attracted toward a position with higher fitness value to reach convergence. Some popular modified versions of PSO have been developed for mathematical optimization and have been occasionally used in swarm robotic source searching task are summarized in Table 2.3.

Table 2.3: PSO and its derivatives in mathematical optimization problem

Type of PSO	Mathematical Expression	Modification
Constriction Factor PSO (CFPSO) (Clerc and Kennedy, 2002)	Velocity update is similar to original PSO but it scaled by κ is the constriction factor, $\kappa = \frac{2}{\left\|2-\phi-\sqrt{\phi^2-4\phi}\right\|}$, $\phi = c_1 + c_2$, $\phi > 4$ where c_1 and c_2 is the acceleration coefficient for cognitive and social, respectively.	Constriction factor κ to guarantee convergence and eliminates velocity limit, v_{max}
Darwinian PSO (DPSO) (Tillett et al., 2005)	Velocity update is similar to inertia weighted PSO (IWPSO) but the following reset is implemented to reset search encounter, *SC*: $SC_c(N_{kill}) = SC_c^{\max}\left[1-\frac{1}{N_{kill}+1}\right]$ N_{kill} is the number of deleted particles	Based on *punish* (deleting particles) and *reward* (introducing new particles) based on *SC* to solve local optima
Standard PSO (SPSO) (Bratton and Kennedy, 2007)	Velocity update is similar to inertia weighted PSO but local neigborhood is considered instead of global neighborhood and the number of particles, *N* are determined as follow: $N = 10 + 2\sqrt{D}$ where *D* is dimension of search space	Replace *global best* with the best previous position in the neighborhood, local best

PSO and its derivatives in general are susceptible to several weaknesses when they are implemented as a source searching algorithm. Pugh and Martinoli (2007) showed that using a constant value of inertia weight throughout the entire searching period may cause robots to oscillate around the target and do not converge to a stable position. In addition, Jatmiko et al. (2011) and Greenhagen et al. (2016) proved that the implementation of PSO with constant parameters in source searching has potential to cause robots being trapped into local optima. Zou et al. (2015) showed that a noisy electromagnetic source seeking using PSO with a damped inertia weight, PSO with a constriction factor and a standard PSO (SPSO) are possible. However, all the three algorithms demonstrate significance target overshooting effect as the robots attempt to converge to the source's position. In addition, they also have not discussed the success rate of the implementation to evaluate the possibility of PSOs being trapped into local optima or slow convergence rate. Akat and Gazi (2008) showed that PSO with a global neighborhood has faster convergence speed as compared to a local neighborhood topology. However, PSO with local neighborhood has been shown having better performance in avoiding premature convergence (Doctor et al., 2004). Gronemeyer et al. (2017) used CFPSO with a fixed communication topology which is robust to premature convergence but it scalability is low due to fixed communication topology. A CFPSO with group dynamic grouping strategy is proposed by Tang et al. (2018) for multiple targets searching. In addition, Melo et al. (2018) studied the impact of different fitness function of a local neighborhood PSO on source searching performance but the study only reliable in simulation as accurate fitness function of the source cannot be found in a real implementation.

Since a direct implementation of PSO has some drawbacks, many modifications and improvements of the PSO and its derivatives have been proposed for swarm robotics source searching task. One of the earliest attempts is performed by Doctor et al. (2004) where the authors investigate the quality factors of PSO parameters (i.e. w, c_1 and c_2). They implement a two-level PSO where the inner PSO is used for target searching task and the outer PSO is used for parameters optimization. The performance is improved but the scalability of the algorithm for large number of robots and premature convergence is not studied. Hereford (2006) proposed a distributed PSO (dPSO) to reduce communication traffic and improved scalability where each robot only broadcast its global best update to other robots if it found a new one. The main weakness of this approach is that for each local robot, both global best and the corresponding position should be updated at the same time to avoid robot stalls. Jatmiko et al. (2006) and Jatmiko et al. (2008) proposed two versions of PSO for odor source localization task, namely detect and response PSO and Charge PSO which were developed based on a constriction factor PSO to solve local optima problem by improving diversity of the swarm. Robot detects the possibility of being trapped into local optima if global best remained constant for a certain number of iterations. As a result, robot responses by reset the global best and repulsive force is used to improve swarm diversity.

The extension of PSO and DPSO for source searching task are known as Robotic PSO (RPSO) and Robotic Darwinian PSO (RDPSO), respectively (Couceiro et al., 2011a, Couceiro et al., 2011b). RPSO is an extended version of inertia weight PSO where the velocity update is modified as follows:

$$\boldsymbol{v}_{\boldsymbol{i}}^{\boldsymbol{k}} = \omega \boldsymbol{v}_{\boldsymbol{i}}^{\boldsymbol{k-1}} + c_1 r_1 \left(\boldsymbol{p}_i - \boldsymbol{x}_{\boldsymbol{i}}^{\boldsymbol{k-1}}\right) + c_2 r_2 \left(\boldsymbol{p}_{\boldsymbol{n}} - \boldsymbol{x}_{\boldsymbol{i}}^{\boldsymbol{k-1}}\right) + c_3 r_3 \left(\boldsymbol{p}_{\boldsymbol{n}}^{\boldsymbol{g}} - \boldsymbol{x}_{\boldsymbol{i}}^{\boldsymbol{k-1}}\right) \tag{2.1}$$

The last term of (2.1) is added to handle obstacle avoidance. Parameters c_3 and r_3 represent obstacle susceptibility weight and the corresponding random vector, respectively. The term $\boldsymbol{p}_{\boldsymbol{n}}^{\boldsymbol{g}}$ is the position of robot n which optimizes monotonically increasing or decreasing sensing function $g(x(n))$. The main purpose of RDPSO is mainly to solve local optima problem encountered by PSO and RPSO by applying social inclusion and social exclusion on the robots based on their level of participation in the searching task (determined by *SC*, see Table 2.3). However, this method requires quite large number of robots to achieve a stable and fast convergence and requires quadruple computational complexity compared to a traditional PSO. Couceiro et al. (2014a) studied the extension of RDPSO considering a systematic initial deployment known as Extended Spiral of Theodorus (EST) and a fault tolerance approach is used to avoid communication network splits. Ranger robots are used to handle deployment of several scout robots to ensure distributed transportation. They found that RDPSO has superior searching performance when EST deployment strategy is implemented but it cannot ensure communication connectivity throughout the searching mission.

Hereford and Siebold (2010) proposed a physically-embedded PSO (PEPSO) where each robot behaves exactly like a particle in PSO except its motion is restricted within a cone instead of a free omnidirectional movement. Robots only share their position if their solution is the best solution. The algorithm is claimed to be able to find a single peak in a complex search space and perform better compared to a basic PSO. Nevertheless, to execute this algorithm robots are required to stop after each iteration to properly handle all relevant information. A mechanical PSO guided by extremum seeking (SE) is suggested by Tang and Eberhard (2013) to account for mechanical properties of the robot and to eliminate precise localization requirement. Since PSO itself is a non-gradient based search algorithm, the ES algorithm provides information about the source gradient to assists PSO. A major advantage of mechanical PSO is it does not require robot localization but disadvantages of the algorithm include robot must have capability to sense state of other robots and it consumes more processing power compared to the ordinary PSO. Rastgoo et al. (2015) combined PSO with *A-star* local search method known as Modified PSO with Local Search (ML-PSO). The algorithm is able to overcome premature convergence (i.e. occurs due to large static obstacle), improve balance between exploitation and exploration to achieve global convergence and reduces searching time. Nonetheless, ML-PSO requires a central station to compute the next position and velocity update for each robot and map of the search space. In the latest extension of RPSO, Dadgar et al. (2016) studied a multi-robot target searching for an unknown environment where an adaptive robotic-PSO (A-RPSO) is proposed. A-RPSO is proposed to solve two source searching problems: to escape local optima and to minimize target overshooting by adjusting inertia weight and acceleration constants adaptively based on swarm aggregation degree and level of fitness improvement. The A-RPSO is proven to be reliable for searching in a large search space with a relatively small number of robots. However, the algorithm is updated synchronously which is less practical when real implementation is required.

Unlike the previously discussed methods where PSO is directly modified, some research works focus on proper abstraction of source information and interpretation especially for sources with dynamic distribution behavior such as chemical odor. A Probability PSO (P-PSO) is introduced by Li et al. (2008a) where PSO with a fitness function is expressed as a local probability estimated by Bayesian and fuzzy inference system is used in attempts to overcome the source intensity fluctuation problem in odor source searching. P-PSO is proved to be able to reduce searching randomness and gives relatively high efficiency in odor searching task. The extended version of their work is performed by Meng et al. (2011) where P-PSO is combined with an estimation method. However, this method tends to fail in a search space fills with obstacles. Similarly, Xue et al. (2009) suggested a fitness function generated from the fusion of multiple sources of signals. However, in some cases a good interpretation of source intensity is not critical if the source is not volatile and can be measured directly such as acoustics, light or heat sources. In these cases, priority is given to improve convergence speed and accuracy of solution by considering relevant information and strategies.

2.3.2(b) Ant Colony Optimization (ACO)

An Ant Colony Optimization (ACO) algorithm is proposed by Dorigo et al. (1999). Ants move randomly to search for food and once the food is found, they lay pheromone on their path as they moving back to their nest. Other ants will track the pheromone left by earlier ants and its strength is intensified if the pheromone lead to a potential food source. As the time passes, the intensity of the pheromone trail decreases due to evaporation. The less the path is followed by the ants, the less attractive the path becomes due to evaporation. The optimum solution is achieved when all or most ants followed the shortest path as illustrated in Figure 2.2.

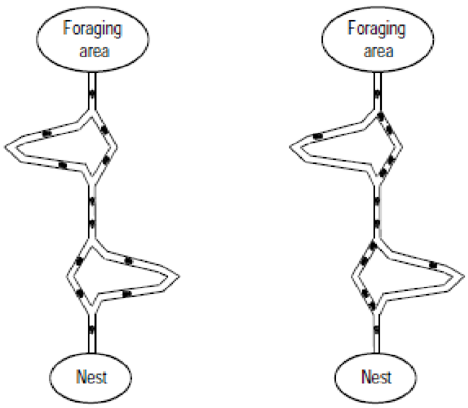

Figure 2.2: Ants shortest path convergence (Dorigo et al., 1999)

In swarm robotic source searching task, Hoff (2011) proposed an algorithm that mimics ACO for foraging task where a wireless communication is used as implicit communication where robot itself acts as a beacon that record the level of pheromone (i.e. contact information). In this method, a beacon robot becomes static and does not contribute to the searching task which may not be effective for a small number of robots. Meng et al. (2006) used an improved version of ACO for odor source localization which consists of three phases: local search based on genetic algorithm (GA), global search and pheromone update. The first two phases are added to ACO to improve performance of the search. GA in local search guarantees optimal or suboptimal points can be found in a local area while random search prevent the ACO from stuck at local optima. However, performance of the algorithm is highly influenced by the initial distribution of the robots. Moreover, Zou et al. (2009) proposed an ACO based odor searching strategy which consists of two parts: tracking strategy and localization strategy. The modified ACO consists of three phases: local traversal search, global search and pheromone update. In order to localize multiple sources, robot that found the source is assigned to the corresponding source while other robots continue their search. Their simulation results show that robots are capable of quickly and accurately trace the sources. Last but not least, Ferreira et al. (2018) studied robots searching behavior similar to ACO inspired by Brazilian Ants where RFID tag is used as pheromone.

2.3.2(c) Artificial Bee Colony (ABC) Optimization

Artificial Bee Colony Optimization (ABC) is initially proposed by Karaboga (2005) to solve multimodal and multidimensional optimization problems inspired by honey bees foraging behavior as illustrated in Figure 2.3. There are three essential