

**ODOUR SOURCE LOCALIZATION STRATEGY
FOR MULTIPLE ROBOTS USING SWARM
INTELLIGENCE WITH ODOUR-GATED
ANEMOTAXIS**

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ANEMOTAXIS**

by

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
ADC	Analogue to Digital Converter
API	Advanced Peripheral Interface
<i>C. lupus</i>	<i>Canis lupus</i>
CFD	Computational Fluid Dynamics
CPSO	Canonical Particle Swarm Optimization
DAPSO	Decentralized Asynchronous Particle Swarm Optimization
<i>E. coli</i>	<i>Escherichia coli</i>
EPFL	École Polytechnique Fédérale de Lausanne
EPSO	Explorative Particle Swarm Optimization
<i>G. stercorarius</i>	<i>Geotrupes stercorarius</i>
GA	Genetic Algorithm
GC	Gas Chromatography
GWO	Grey Wolf Optimizer
I ² C	Inter-Integrated Circuit
LGSA	Large Gas Sensor Array
MOX	Metal Oxide Gas Sensor
NDIR	Non-Dispersive Infrared
PACO	Parallel Ant Colony Optimization
PGWO	Parallel Grey Wolf Optimizer
PID	Photo Ionization Detectors
PLIF	Planar Laser-Induced Fluorescence
PSO	Particle Swarm Optimization

QCM	Quartz Crystal Microbalance
VOC	Volatile Organic Compound
WSN	Wireless Sensor Network
1D	One Dimension
2D	Two Dimension
3D	Three Dimension
-CS	Continuous Sampling
-OG	Odour Gated Anemotaxis

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LIST OF SYMBOLS

A_{ij}	Reactive swarm attraction force between robot i and j
b_i	Best position of the i^{th} robot
B_i	Braitenberg motion vector of robot i
C_{avg}	Average of the searcher robots
C_i	Maximum gas sensor reading obtained during local search
D_{ij}	Euclidian distance between robots I and j
G_a	Attractive gradient to waypoint for robot i
G_t	Total potential field
G_r	Repulsion gradient
g_i	Position of the global best
h_i	Factor of wind vector from robot to estimated wind source
I	Gas sensor time dependent response model
I_a	Actual gas sensor response
I_f	Initial gas sensor response at falling edge
I_r	Initial gas sensor response at rising edge
i	Sensor signal
$J_{a,i}$	Attractive potential for robot i
J_r	Repulsion potential
n	Row number of LGSA
p_i	i^{th} robot waypoint
\vec{p}_{ij}	Vector from robot j to robot i
P_{ij}	ACO probability rate migration

\vec{p}_i	Vector from current waypoint to the next waypoint
Q	Intersection of the lines in the direction of two airflows
R_s	Gas sensor resistance
R_0	Gas sensor baseline resistance
t_n	Data stream time
t'	Simulation time
x_i, y_i	i^{th} robot coordinate
v_i	i^{th} robot linear speed
w_x, w_y	Wind vector element
\vec{w}	Normal vector in the direction of airflow
\vec{x}	GWO position of a robot
\vec{x}_p	GWO position of the prey
λ	Decay rate
λ_f	Decay rate of falling edge for gas sensor signal
λ_r	Decay rate of rising edge for gas sensor signal
η_{ij}	ACO heuristic function
τ	Exponential decay time constant
τ_j	Pheromone level of searcher robot j
ω_i	i^{th} robot angular speed
θ_i	Orientation of robot i
χ	PSO constriction parameter
φ_1 and φ_2	Learning coefficient
ρ	ACO pheromone constriction coefficient

Strategi Penyetempatan Sumber Bau Untuk Berbilang Robot Dengan Kepintaran Kerumunan dan Anemotaxis Dikawal Bau

ABSTRAK

Haiwan seperti kupu-kupu ulat sutera, anjing dan ketam biru mempamerkan kebolehan untuk mengesan sumber bau secara semulajadi. Kebolehan ini pula dilakukan di dalam pergerakan udara yang kompleks, yang menghasilkan penyebaran gas yang sangat dinamik dan tidak dijangka. Dengan adanya kebolehan tersebut, robot-robot boleh diaplikasikan untuk kerja-kerja kritikal dan bernilai tinggi seperti operasi menyelamat, kawalselia di pusat kemasukan asing, dan pemerhatian alam sekitar di kawasan perindustrian dan bandar. Thesis ini mendokumenkan kajian mengenai kepintaran kerumunan untuk penyetempatan sumber bau. Penggunaan kepintaran kerumunan untuk menangani kerja tersebut dijangka lebih praktikal dan ekonomikal berbanding sistem robot tunggal. Buat masa ini, tidak banyak kajian telah dibentang berkenaan sistem berbilang robot untuk penyetempatan sumber bau. Kajian ini bertujuan untuk memenuhi kerompongan kajian untuk strategi penyetempatan sumber bau dengan menggunakan kepintaran kerumunan. Walaubagaimanapun, kaedah penyelidikan yang telah dibuat dalam bidang ini terlalu memudahkan permasalahan sebenar, lantas mengurangkan impak penyelidikan dalam memajukan bidang penyelidikan ini. Tambahan pula, kaedah experimental yang kurang realistik mengurangkan kebolehulungan kajian-kajian yang terdahulu. Untuk megatasi kekurangan tersebut, kajian ini menggunakan penyebaran bau yang direkod dalam masa sebenar bagi simulasi robot. Sebuah sistem pemerhatian penyebaran gas secara masa nyata, terdiri daripada 72 sensor gas, telah dibina untuk merekod sebaran gas di dalam kawasan eksperimen. Data yang telah direkod kemudiannya digunakan di dalam simulasi untuk mewujudkan suasana eksperimen sebenar dalam simulasi. Simulasi tersebut kemudiannya digunakan untuk menguji kebolehan algoritma kepintaran kerumunan berbeza, di samping membekalkan kekuatan statistik. Tiga algoritma kepintaran kerumunan terkemuka, Particle Swarm Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) dan Grey Wolf Optimizer (GWO), beserta dengan versi selarinya, telah diimplemen. Kebolehan algoritma-algoritma tersebut untuk menjejak bau dan memanjat kecuraman konsentrasi gas dengan bilangan agen yg berbeza telah dikaji. Kemudian, penambahbaikan telah diperkenalkan kepada algoritma-algoritma tersebut. Pembedaan masalah ini berbanding bidang sains komputer dan masalah pengoptimuman biasa membenarkan implementasi penyampelan berterusan untuk kepintaran kerumunan. Seterusnya, kaedah novel untuk mengimplemen anemotaxis bagi kepintaran kerumunan telah diperkenalkan. Penambahbaikan tersebut telah berjaya menghasilkan kebolehan pengesanan sumber bau dengan lebih tepat. Akhir sekali, berdasarkan pemerhatian algoritma-algoritma kepintaran kerumunan terdahulu, sebuah algoritma baru telah diimplemen. Algoritma tersebut berjaya mempamerkan kebolehan yang lebih baik berbanding algoritma kepintaran kerumunan. Kajian yang didokumenkan di dalam thesis ini berjaya menjawab beberapa persoalan dalam pelaksanaan sistem pemerhatian alam sekitar dan merapatkan jurang bagi melaksanakan sistem robot kerumunan sebenar.

Odour Source Localization Strategy For Multiple Robots Using Swarm Intelligence With Odour-Gated Anemotaxis

ABSTRACT

Animals such as silkworm moths, dogs and blue crabs have exhibited odour localization capabilities in nature. This amazing ability is exhibited in complex airflow conditions which produces highly dynamic and unpredictable gas dispersion. Harnessing this capability will enable robots to be deployed in critical and high-value applications such as search and rescue, entry point security applications, and environmental monitoring in industrial and urban settings. This thesis documents the research in swarm intelligence for gas source localization. Using swarm intelligence to achieve this task is envisaged to be more practical and economical compared to single robot implementations. Currently, few works have been presented on multi-robot systems in gas source localization; much less using swarm intelligence. This research aims to fill in the research gaps in gas source localization using swarm intelligence. However, current mobile olfaction experimental methods tend to oversimplify the actual problems thus reducing the findings' impact in advancing this research field. Furthermore, lack of experimental realism reduces the reproducibility of the previously presented works in real world conditions. To overcome this limitation, this research uses recorded real-time gas dispersion in robot simulations. A real-time gas dispersion monitoring system consisting 72-gas sensors was built to record the gas dispersion in the experiment area. The recorded real-time data stream was then used in simulations to accurately recreate real-world experimental conditions in a simulation environment. This simulation environment would then be used to objectively assess and evaluate the performance of different swarm intelligence algorithms while providing substantial statistical strength. Three standard swarm intelligence algorithms; namely, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Grey Wolf Optimizer (GWO), and its parallel variations are implemented. The plume tracing and gas concentration climbing ability of the algorithms in different agent numbers are studied. Next, enhancements are introduced to the algorithms. First, the detachment of this task from computer science and typical optimization problems allows continuous sampling to be implemented in the swarm algorithms. Next, a novel method to implement odour-gated anemotaxis to swarm intelligence was implemented. With the introduction of the enhancements, the algorithms have been shown to produce more accurate gas source localization capabilities. Finally, based on the observed behaviours of the swarm intelligence algorithms, a reactive swarm algorithm was implemented to capture observed favourable behaviours for gas source localization. The proposed reactive algorithm was able to outperform the swarm intelligence algorithms; although showing some robustness issues. The work presented in this thesis is able to answer some issues in widespread implementation of environmental monitoring and lessens the gap to full swarm system deployment in real world.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Animals with relatively low levels of intelligence such as dogs, silkworm moth, lobsters and blue crab have all exhibited odour source localization capabilities for hunting, foraging and mating (Fraenkel & Gunn, 1961). Remarkably, these simple beings are able to complete their task in an unknown environment in which unpredictable airflow affects the odour dispersion. The ability to track and find odour sources has enabled these animals to maintain the continuity of their species. This feat; although appear to be simple, is yet to be fully imitated by synthetic systems produced by humans. Being able to replicate this skill in robots may offer deeper understanding of animal behaviour and opens up the possibility to use the knowledge gained in many applications. Motivated by the myriad of potential applications based on gas sensing and localization capability, a considerable amount of interest has been generated in this research field.

The search for hazardous or explosive substances, locating prohibited drugs at international entry points, early detection of fire, detecting biological entities in either search and rescue scenarios or quarantine applications and are some of the possible applications envisaged to benefit from advancements in this research field. The development of strategies for gas source localization and applying it to an appropriate robot system may ease the dependency on trained dogs and removes the need for direct human intervention in hazardous and risky situations. There would be no need for dogs

to be trained for years in the art of bomb or drug detection, or needing humans to sample hazardous gas levels to predict the location of a leak in a petroleum plant. Furthermore, implementing gas localization on robots will allow a new medium of communication between robots in a swarm.

The need for gas localization capabilities can be seen in the amount of accidental poisonings and deaths recorded around the world. The conventional method would be to place gas detectors in designated places which require the deployment of a large amount of gas sensors (Jung-Yoon, Chao-Hsien, & Sang-Moon, 2014). As these gas sensors need to be maintained and recalibrated periodically, comprehensive deployment of static gas sensor arrays is so far unfeasible. Furthermore, the detection of low concentrations of gas is difficult in such deployments as; depending on the type of sensor used, the variations in environmental conditions and sensor drift more often than not mask the small changes in concentration. This is dangerous in the case for Carbon Monoxide; as prolonged exposure to even low concentrations can damage brain functions. Robots with gas sensing capabilities can monitor gas in a large area and localize its source if needed. Service robots are already being deployed for other functions. Adding another task to these robots for monitoring and emergency response would be cost effective. These robots may reduce the amount of gas sensors needed; thus lowering maintenance and calibration requirements. Also, as the sensors may be calibrated more frequently, the detection of low concentrations of gas is feasible and more accurate. Hence, an intelligent robot system which can respond to abnormal gas levels and localize the gas source is needed to realize such applications.

1.2 Research Motivation

The gas localization problem has only been researched by the academic community since less than three decades ago and has generated great interest ever since. The wide variety of disciplines involved adds complexity to this research field; needing the involvement of various intellectuals with different backgrounds. The gas localization task can be broken into a few sub-tasks (Lilienthal, Reimann, & Zell, 2003):

- a) The search for the target gas plume
- b) The tracking of the gas plume
- c) The declaration of the gas source

Most of the effort in gas localization is focused on the second task where the integration of various science disciplines is most vigorous.

Gas source localization problem is known to be complex due to the erratic movement of gas in air. The type of dispersion can be predicted by the Reynolds number of the flow. At low Reynolds number, the fluid flow would be laminar; thus diffusion of the gas is the dominant factor in the gas dispersion. The gas concentration would be high at the source and decrease farther from the source, according to Gaussian distribution (Hinze, 1975). However, this condition very rarely happens in real world, where a solution for the gas source localization task is pursued. In fact, diffusion dominated dispersion are mostly observed at micro levels; only microorganisms experience this sort of dispersion. At medium to high Reynolds number, turbulence conditions occur; eddies and vortexes forms in the air flow. The significant airflow causes advection to dominate the gas dispersion whereby the gas is carried by bulk flow and mainly dispersed by the fluid movement. This causes uneven dispersion of the gas