

## GLOBAL JOURNAL OF ENGINEERING SCIENCE AND RESEARCHES SEMI-PHYSICAL SIMULATION ENVIRONMENT FOR ROBOTIC ODOR SOURCE LOCALIZATION

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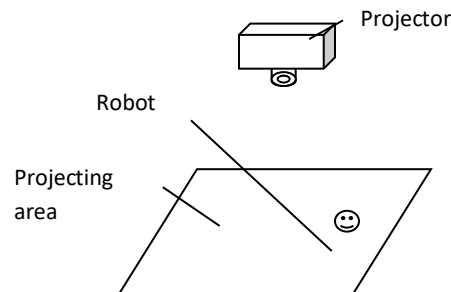
### Abstract

With the complexity of odor source plume focused on, the data of plume distribution which is visualized by a sequence of images using Open DX, a visualization software, is obtained by Fluent, a hydro mechanical dynamic modeling software, computing the odor concentration of the field interested. The sequence of images was projected to the ground to form a virtual dynamic odor distribution environment where the light intensity indicates odor concentration. To research mobile robot olfactory with semi-physical simulation environment consisting of the images mentioned above and a robot equipped with light sensors, the authors make robot to locate the odor source by traveling the plume. To acquire the semi-physical simulation environment performance, adopting moth-algorithm, we conduct an experiment which result show the repeatability, environment friendliness and close to natural environment.

**Keywords:** Robot, semi-physical, Odor source localization, Simulation environment.

### I. INTRODUCTION

In the last decades, the robotic research community has advanced the intelligent machine capable of many works, especially in industrial manufacture where are lots of dull operations done by robotic arm. Researchers devote themselves to develop some robot with human skill for dirty, dull and dangerous work (namely 3D-work) such as operation repeating, mess room clearing and dangerous substance locating[1-2]. Yet to date, scientists have not make robot containing all the abilities of human or even of animals. One of the greatest challenge to researchers is to develop robotic olfaction for odor source localization, an increasing hot topic recently. Many research teams struggle forward in robotic odor source localization. However, the progress is far away from it's application. Most of those teams aim at algorithm development and optimization, namely structuring or optimizing an algorithm and then testing it to obtain the efficiency and probability. Therefor many algorithms, such as GA(genetic algorithm), NNA (natural net algorithm), SA (simulated annealing algorithm), PSO (particle swarm optimization) etc., had



*Figure 1 the structure of semi-physical simulation environment of robotic odor source location*

been modified or even optimized for odor source localization and demonstrated its' efficiency and probability with experiment in natural environment [3-7].

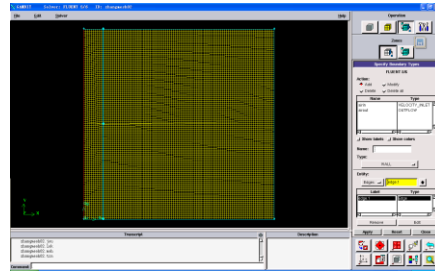


Figure 2 grid of field interested designed with Gambit

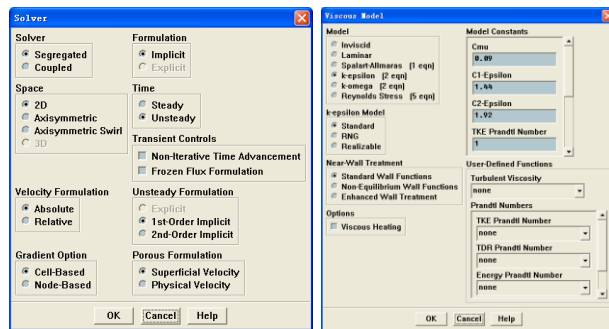
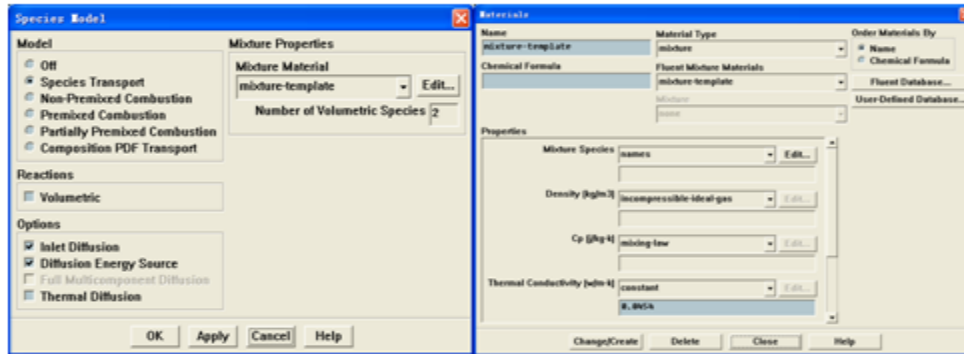


Figure 3a solver setting Figure 3b viscous model setting

Testing different olfaction navigation strategies in real world is time consuming and presents low repeatability among experiments. Simulation can resolve some of these problems replace the need for fabrication of prototype robot with simulator software which making researchers' repeat of testing and modifying their algorithms easier and possible before satisfactory performance obtained. But there is no special simulator for robotic odor source location because of the most difficulty of presenting realistic odor plume in virtual environment. Farrell et al. developed the odor plume model which is the first and a popular one for plume-tracing research using mobile robot [8]. This plume model was named the filament-based atmospheric dispersion model. It included a continuous wind field which covered the region of interests and the wind vectors varied with location and time in this region. The odor plume is present a sequence of puffs consisted of many filaments whose shape, size and location are determined by wind vector (the sequence of puffs). With the various puffs, the filaments with different shape, size and location form the plume vary by time in the simulating field. This plume model is so simple that it is quite different from real plume propagation process and the sensor output varies sharply as the sensor caught the filament in robot simulation research. With using software Matlab combined with CFD (Computational Fluid Dynamics software) , a commercial software provided by Fluent, Inc. Zhenzhang Liu developed a simulation framework for plume-tracing research [9]. In this framework, the plume model was obtained by using Fluent software which consists of Gambit, a component for structuring grid, and fluent, a hydromechanics dynamic solver, and the data of odor distribution was export from Fluent and import into Matlab for simulation. This framework represents the odor source of distribution of real world more dependable then filament-basic model. Robotic researchers could develop some robotic odor location algorithms and test them basic on this virtual environment for their efficiency, convergence and success rate



*Figure 4a species model setting*      *Figure 4b material model setting*

without robot-prototype fabrication. However, Zhenzhang Liu did not give the detail of structuring the environment in his paper and the generality is poor because of the variation of the field interested.

This paper focuses on structuring a virtual environment for robot odor source location with high-generality and detailing critical developing-step for robotic research community of odor source location easily constructing simulation-environment and it is organized as follows : a representation of semi-physical simulation environment structure, building the grid of field interested and its boundary condition with Gambit software and details of development approach of odor-plume model using Fluent in Section 2. Section 3 represents a Moth-algorithm-applied-example simulation in the semi-physical simulation environment of robotic odor source localization. In Section 4, discussion and conclusion are made.

## II. CONSTRUCTION OF SEMI-PHYSICAL SIMULATION ENVIRONMENT OF ROBOTIC ODOR SOURCE LOCALIZATION

### 2.1 Synopsis of semi-physical simulation environment of robotic odor source localization

In robot olfactory study, researchers, to test robot and its algorithm application effect, let robots track the plume formed with odor source distribution in air environment to locate the odor source [10]. This approach is characterized not only by its advantage simulating real world where robot would be applied for active olfactory, but also by its disadvantages such as the toxic properties of the gas poisoning researchers in simulation field, the one-off of this kind of environment that it can't be reused, and the additional cost of continuously releasing these gases [11,12]. In addition, colorless odor plume also is not friendly to understand the detail of robots search process. For researchers to test the robot and its algorithm viability, this paper presents a semi-physical simulation environment consisting of mobile robot and optical plume produced by a projector projecting a set of images which, using OpenDX (a kind of visualization software), were formed with plume data exported from Fluent (a kind of computational fluid dynamics [13,14]). The building process can be summarized as follows : first, a period of odor plume distribution in interested field is computed in Fluent and instantaneous data is exported as .dx files. Second, import the data files exported from Fluent into OpenDX and visualize it into a sequence of image files. Last, using a projector, project the images to the ground continuously to lead the robot to the virtual odor source. Figure 1 illustrates the structure of semi-physical simulation environment of robotic odor source localization.

### 2.2 establishment of odor plume model

Fluent, a kind of computational fluid dynamics (CFD) software developed by Fluent soft company and widely adopted in fluid modeling, is applied to calculate the distribution of odor plume in air in the interested field which is

usually simplified as a 2-dimension problem [11]. First, the interested field grid is constructed in Gambit (illustrated in Figure 2), a component of Fluent software, and some of the boundary conditions of the field, such as inlet, outlet and source type, are defined because of Gambit only involving simulation regional boundary condition. Generally, the inlet condition is delimited as velocity-inlet, outlet as outflow, source type as fluid and others as default that the boundary lines of the field would be set as wall and all the lines inside the field would be deleted. After all the above is done, we can export the grid of the interested field to a file with .msh extended-name. Then we import the .msh file into Fluent and set solver type illustrated in Figure 3a, viscous model shown in Figure 3b and species model demonstrated in Figure 4a and material illustrated in Figure 4b in turn.

Considering the irregular change of the wind speed and direction, we do not set the inlet condition as one of velocity-inlet parameters the Fluent provides, but the one we define (user define function, UDF), that the wind speed and direction change randomly to make the plume model more similar to reality. The velocity-inlet parameter, wind vector defined by UDF here, consists of wind speed of X direction and speed of Y direction analogously programmed with C language. The X direction procedure are given as follows :

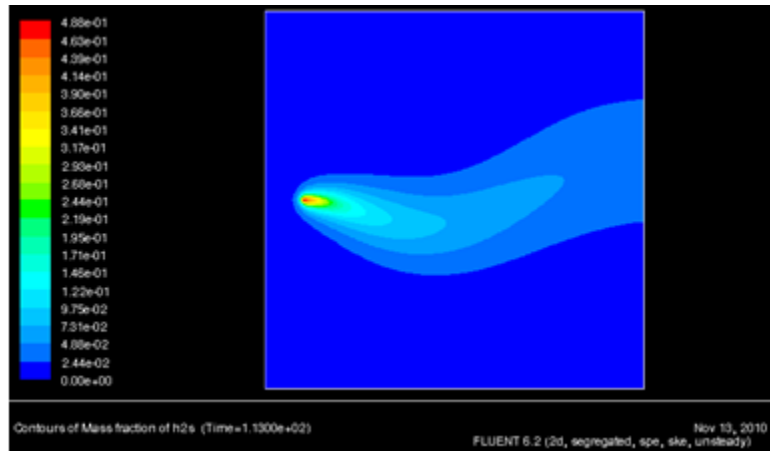
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/*vxprofile.c*/
#include "udf.h"
#include "stdlib.h"
DEFINE_PROFILE(inlet_x_velocity,thread,position)
{
    face_t f;
    real t=CURRENT_TIME;
    real alpa;
    unsigned int i;
    real velocity;
    srand(t);
    i=0;
    alpa =22.5*sin(10*t*3.14/180);
    begin_f_loop(f,thread)
    {
        if(i%4==0)
            velocity=rand()%8;
        F_PROFILE(f, thread, position)=velocity*cos(alpa*3.14/180);
        i++;
    }
    end_f_loop(f,thread)
}

```

Having defined the two UFDs above, we can compile and load them in Fluent. Note that the C compiler must be installed into the computer because of using it to compile the procedures.

After all aforementioned were done, the iteration operator, the Fluent solver, can be launched to obtain the odor plume distribution data which will be saved on hard disk as ASCII files (for Matlab simulation ) and .DX (OpenDX data format) files in each iteration step. The number of iteration step is defined according to simulation need of the simulation environment. For instance, assuming the robot could find the virtual odor source in the simulation environment within 100 steps or iterating the 100<sup>th</sup> step indicates that the robot fails in locating the virtual source in the simulation environment, we can let N (the number of iteration step) = 100. However, there should be a margin steps for simulation which always ranges from 20 to 50 [10]. so, in this case, we may set N=120. In each iteration step, there will be a ASCII file to save the odor plume distribution obtained by iteration operator and a image (contour model) to refresh the display window illustrated in Figure 5.



*Figure 5 odor plume distribution obtained by iteration operator and displayed in Fluent display windows with contour model*

Developed for computational fluid dynamic modeling, Fluent software is adept at computation and model construction, yet not at plotting [15]. This is demonstrated in the Figure 5 in which the contour lines are vividly shown that makes the image different from realistic odor plume distribution which concentration (the color here) varies gradient in strong wind field [16]. Consequently, we apply OpenDX, a kind of free software developed by IBM for science computation data visualization, to picture the odor plume distribution. In this process, obtained by Fluent iteration operator, each odor plume distribution data file was imported into OpenDX to produce image which was saved on the hard disk as .tif file and illustrated in Figure 6. All the .tif files constitute a sequence to project according to its number of iteration step. Hence, there will be a virtual odor-plume-animation in the projecting field where the dynamic light intensity indicates the odor concentration. Note that the image projecting model should be set as grey-scale in the projector parameters setting menu. In the simulation process, equipped with light intensity sensor to perceive light intensity (means the odor concentration in real world) of its location, according to variation of the odor concentration combined with the applied algorithm, the robot would locate the odor source (the highest light intensity) in the projecting field. So much for that, we have built the simulation environment for robotic odor source localization research and another simulation environment which based on the data files and pictures above and Matlab mentioned by zhenzhang Liu can be easily derived.

### 2.3 robotic selection and modification

This paper selects PALBO-TEP06, a rough mobile wheel-robot with tracking, tracing and obstacle avoidance function produced by Tianjin PALBO company. The robot was reequipped with two a light-intensity-sensors, TSL2561, on both sides of its top separately to sense the light intensity (odor concentration in real world) and a wind direction detector to acquire wind direction in simulation environment. Therefore, wherever the robot travels, the odor concentration and wind direction will be obtained by the sensors.

## III. REALIZATION OF ACTIVE OLFACTORY ALGORITHM IN THE SIMULATION ENVIRONMENT

### 3.1 Algorithm selection

In this study, with obviously good performance compare to Casting algorithm and slightly superiority to Surge-spiral algorithm, the Surge-cast, a novel active olfactory algorithm for odor source finding and localization in windy environment presented by Thomas Lochmatter and Alcherio Martinoli, was selected to test this novel simulation environment [17]. Those algorithms mentioned above are inspired by the approach that male moths search for

female ones by sensing the pheromone concentration released by the females. The male moth search strategy is : if it has been in the phenomenon plume, the male moth would not stop fly upwind until out of the plume, called Upwind surge. On flying out of the plume, the male moth would switch to fly cross wind in zigzag way till reaching the plume or declaring failure after which the search model would be changed to Spiraling indicating that the male moth would reacquire the plume in an irregular spiral way. All the three algorithms above, Surge-casting, casting and Surge-spiral, are combination of Surge, casting and spiral strategies [18-20].

Actually, Surge-cast algorithm, illustrated in Figure 7, is a combination of Upwind-surge and Casting strategies. In this algorithm, the behaviors of robot to search for odor source consists of searching upwind and searching crosswind [21-23]. The former means that the robot would search for odor source with Upwind surge model in the plume till it steps out of the plume for a defined distance  $d_{lost}$  and the latter indicates that it would reacquire the plume with Casting model by which the robot would not stop moving in zigzag way until into the plume for a defined distance  $d_{cast}$  where it would switch back to Upwind surge again. The repeating of two-strategy-switch would play continuously till the robot catches the end of the plume, odor source, or was stopped to declare failure in searching.

### 3.2 Algorithm realization

Combined with Surge-casting algorithm programmed in C language, the robot runs in the simulation environment. To facilitate our work, these following compromises were employed for testing the viability of this semi-physical simulation environment:

- It is considered that the robot succeeds in odor source localization when the distance between it and the source is shorter than 20cm.
- Near the source, a fan is used to build a continuous wind flow through the simulation field to guide the robot by its sensing the wind direction.
- A little threshold value was set for judging whether the robot is in the plume or not by sensing light intensity.
- The parameters ( $d_{lost}$  and  $d_{cast}$ ) are replaced with times ( $t_{lost} = 2$  seconds,  $t_{cast} = 1$  second) the robot covers these distance separately.
- Given its vainly searching times is longer than 5 minutes, the process would be stopped and declared its failure.

With the preparing and configuration mentioned above, we experiment for 20 times in simulation field of 5m long and 4m wide and the result is that the robot succeeds in localizing the odor source for 17 times, 3 failures. The longest consuming-time is 3'46" and shortest one is 2'32".

## IV. DISCUSSION AND CONCLUSIONS

Odor plume model of windy environment was built and result of each iteration step was saved as data file and image file which would be projected to reproducing the odor distribution environment with light-intensity corresponding to odor concentration. Hence, sensor to detect the light intensity in simulation is similar to measuring odor concentration in natural environment. The viability of the semi-physical simulation environment is confirmed by the result of experiments done in it with a reequipped robot collaborating with Moth Algorithm.

The advantages of this simulation environment are: a novel method, projecting odor distribution image to construct plume simulation environment, is presented for active olfactory research that corrects the shortcoming of light simulation environment mentioned by Zhenzhang Liu, Tien-Fu Lu that it cannot describe the odor turbulence. The robot search behavior in this environment is more likely in real world. The plume simulation data generated in Fluent can be reused as many times as the researchers prefer. Therefore, researchers do not need to repeatedly spend time on plume model development and can focus on the development of the plume-tracing algorithms. Additionally, there is no pollution absolutely in this environment and the cost is reduced yet versatility improved by replacing the costly odor sensor with light sensor.

However, there are some limitations of using this simulation environment. First, researches should be familiar with Fluent and OpenDX and know the basics about how to simulate plumes using Fluent and to convert the model data

into image. Second, in this study it was assumed that the size and the motion of the mobile robot did not influence the plume propagation while the robot was tracing the plume in the semi-physical simulation environment. However, this is not really true especially when the size of the robot is relatively big and travels at higher velocities. All these shortcomings may reduce the reliability of the simulation results in this semi-physical simulation environment. In future, we will overcome these shortcomings to improve the performance of the semi-physical simulation environment.

## V. ACKNOWLEDGMENTS

The authors would like to thank Ms. Zhang Yu-li who comes from Dalian Jiaotong University for her valuable suggestions and direction on this paper.

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