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Proceedings of the 1st Chinese-Austrian Workshop on Environmental Odour: Emission-Dispersion-Impact Assessment

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The general objective is to promote and extend the use of statistical and mathematical methods in veterinary epidemiology. Special emphasis is given on methods and results. Monographs, paper collections or conference proceedings will be published in German as well as in English in the Austrian Contributions to Veterinary Epidemiology if judged consistently with these general aims. All contributions will be refereed.

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Preface

In the last decades, environmental unpleasant odours have become a serious concern caused by the awareness of the population in respect to human health and wellbeing issues. Odour exposure may short time not acutely represent a risk for human health, but the exposure causes different negative effects, ranging from emotional stress to physical symptoms. As a matter of fact, environmental odours are considered to be major causes of public complaints. Residents living near odour emitting sources complain to local authorities, regional or national environmental agencies or directly to the personnel involved with the odour-emitting source for problem reduction or elimination. Therefore odour is on the top agenda in the field of air quality programs of environmental agencies all over the world.

In general odour emission can be handled like any other airborne pollutant. Starting with the release of the odour at an emission rate depending on the source, the emitted odorous substances are dispersed in the atmosphere. This dilution process can be calculated by various dispersion models, which permit the assessment of the odour exposure. By national odour impact criteria this exposure is calculated to decide if odour annoyance can be expected at a certain site. The odour chain, which starts with the emission and ends with the perception of a resident, was the framework of the 1st Chinese-Austrian Workshop on Environmental Odour held in Tianjin, China in February 2015. The contributions to this workshop are published in this issue of the *Austrian Contributions to Veterinary Epidemiology*. The workshop was successful to stimulate the dialogue between China and Austria on air pollution and to develop innovative and successful strategies to handle environmental odour.

This bilateral meeting laid paths for the community of scientists involved in odour assessment to achieve a better understanding of the specific aspects connected to odour problems. The major goal was to stimulate research activities and co-operations in the field of environmental odour.

The workshop as well as the current publication of the Austrian Contributions to Veterinary Epidemiology was funded by *Eurasia-Pacific Uninet* as a network which aims at establishing contacts and scientific partnerships between Austrian universities and member institutions in East Asia, Central Asia, South Asia and the Pacific region. This Chinese-Austrian workshop was hosted by Prof. Dr. Qing-Hao Meng at the School of Electrical Engineering and Automation, Tianjin University. He and his team deserve gratitude for the successful organisation on site and his Austrian counterpart Prof. Dr. Günther Schauberger from the University of Veterinary Medicine Vienna for initiation and organisation of the meeting. Both were the guest editors for this issue.

I hope that this workshop is an incentive for a fruitful and long-lasting scientific exchange between the two countries.

Prof. Dr. Wolf-Dieter Rausch
President of the Eurasia-Pacific Uninet

Vienna, November 2015

Spatial distribution of odorous compounds in an enclosed waste mechanical biological treatment plant

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The concentrations and species profiles of gaseous pollutants emitted from a municipal solid waste (MSW) treatment plant were investigated to identify the major odorous substances. Three methods were used to measure different gaseous pollutants in this study, including gas-chromatography with mass spectrometry/flame ionization detection/pulsed flame photometric detection (GC-MS/FID/PFPD) preceded by cold trap concentration, GC-FID preceded by sorbent concentration, and high-performance liquid chromatography (HPLC) after derivation by 2,4-dinitrophenylhydrazine (DNPH). Seventy-five gaseous compounds belonging to nine groups (nitrogen compounds, sulfur compounds, alkanes, alkenes, aromatics, terpenes, alcohols, carbonyls, and volatile fatty acids (VFAs)) were identified. The major odour compounds in the plant were acetic acid, butyric acid, valeric acid, isovaleric acid and dimethyl sulfide.

1. Introduction

Mechanical biological treatment (MBT) technology could benefit resource and energy recovery from municipal solid waste (MSW), as well as the reduction on the landfilled amount of biodegradable waste. In recent years, MBT has been widely used in European countries (Calabro et al., 2007). For example, 6.35 million tons of MSW were treated by MBT technology in Germany (Weidemeier, 2007). MBT technology has also been used in some developing countries, including China (in Beijing and Shanghai City) (Tränkler et al., 2005). Due to dietary habits, the contents of organic matter and moisture in MSW in Asian countries are usually relatively higher than those in European and North American countries, which may induce more secondary pollution (i.e. leachates and gaseous pollutants) (Norbu et al., 2005; Pierucci et al., 2005). The gaseous pollutants mainly include inorganic compounds such as ammonia, hydrogen sulfide, as well as a large number of extremely complex volatile organic compounds (VOCs), most of which are toxic and hazardous and classified as priority pollutants in the United States, Europe, Japan and China (Bockreis and Steinberg, 2005; Karageorgos et al., 2005).

Studies of gaseous pollutants released during the MSW treatment process have primarily been focused on two aspects, i.e., the characteristics of gaseous pollutants and their impacts on the environment, and occupational exposure (Tolvanen et al., 2005; Domingo and Nadal, 2009). Among gaseous pollutants released in a waste composting plant, ammonia was found to be predominant, with an emission of around 18−1150 g/t waste (Clemens and Cuhls, 2003). The ammonia concentration in the exhaust gases of a sewage sludge composting plant was as high as 700 mg/m^3 (Cadena et al., 2009). Other important compounds were VOCs, which had been detected with concentrations ranging from 10 mg/m^3 to 15 mg/m^3 in the air in MSW composting plants (Eitzer, 1995).

Citation: Fang J., Lü F., Zhang H., Shao L., and He P. (2015): Spatial distribution of odorous compounds in an enclosed waste mechanical biological treatment plant. Austrian Contributions to Veterinary Epidemiology. Vol. 8, 7-14.

Rodriguez et al. (2010) investigated the impacts of operating parameters (moisture, oxygen and C:N ratio) on the release patterns of VOCs during a composting process and found that the C:N ratio was the most important factor, followed by the internal oxygen and moisture contents of the waste pile.

During the waste composting process, incomplete or inadequate ventilation could cause significant releases of odour substances such as hydrogen sulfide. Mao et al. (2006) found that dimethyl sulfide, dimethyl disulfide, limonene and α-pinene were the main odour substances in a MSW composting plant. A study conducted in a food waste composting plant by Tsai et al. (2008) showed that the relationships between concentrations and odour intensities of ammonia, dimethyl sulfide and acetic acid were logarithmic, while those of acetic acid, ethyl benzene and p-cymene were linear. It has also been reported that trimethylamine could be perceived and detected at greater distances than ammonia due to its higher persistence and lower odour threshold (Thriel et al., 2006).

This study investigated the spatial distribition of gaseous pollutants outside the treatment facilities of a MBT plant in Shanghai. Based on the concentrations, the main distributions of the pollutants of the plant were simulated and identified through the contour profiling.

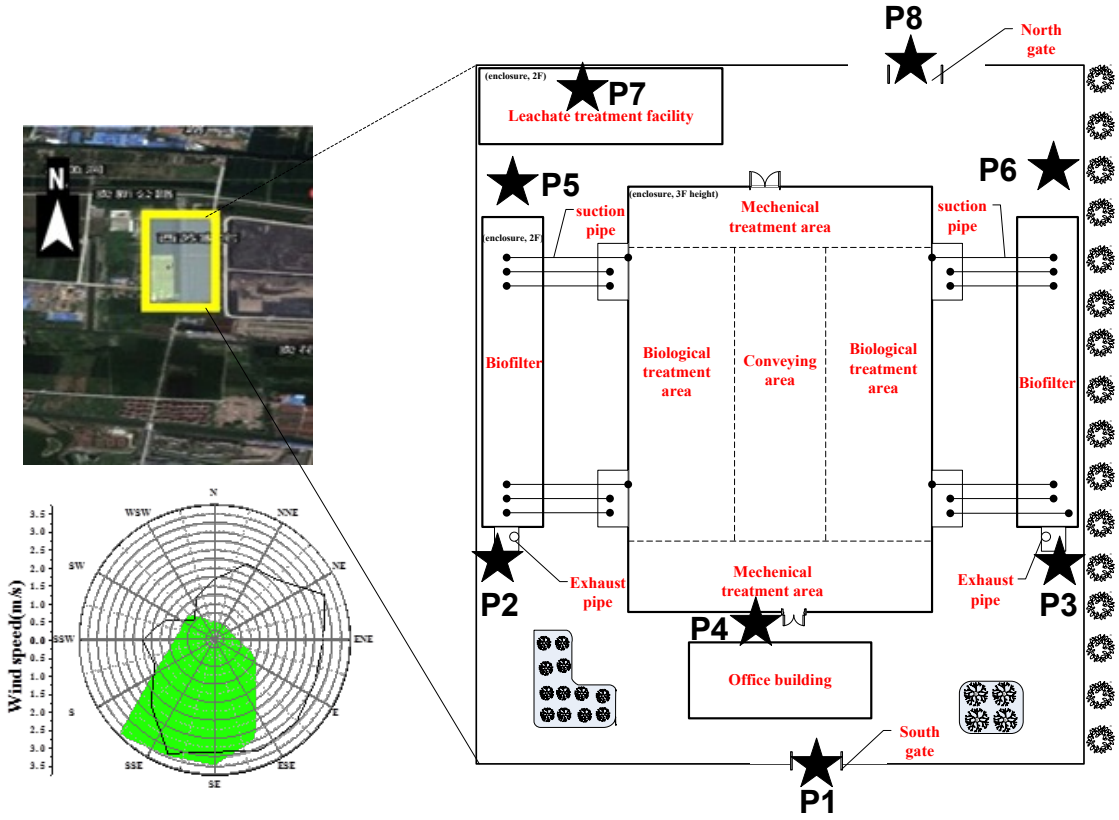

Figure 1: Arrangement of sampling points in the treatment plant and the wind-rose chart during the sampling campaign (left bottom). "P1-P8" with stars, represents the sampling points. The shadow area in the wind-rose chart represents the wind direction frequency and the curve represents the wind speed.

2. Materials and methods

2.1 Site Description and sampling location

The MSW treatment plant was 1200 t/d, with a working area of 20,000 m^2. A schematic diagram of the treatment processes is shown in Fig. 1. Briefly, MSW was delivered from the north gate to the mechanical treatment facility, where the waste was sorted manually, then size-separated using trommel screens. After the mechanical treatment, the waste was conveyed to the biotreatment facility for 20 days of aerobic fermentation. Next, the waste was sorted again in mechanical treatment facility, after which undersized material was delivered to a biotreatment again for another 30−60 days of aerobic fermentation. Two biofilters were located symmetrically on the left and right side of the treatment facilities. On the north of the plant, there was the leachate treatment facility. These facilities were all enclosed. The odour compounds inside the treatment facilities had already been discussed by Fang et al. (2013), while this present study focused on the surrounding circumstance outside the above-mentioned facilities in the plant. Two points were arranged on the south and north gate (P1, P8), two points were arranged in the exhaust pipe on the monitoring platform (P2, P3), one point was arranged between the facility and office building (P4), one point was arranged on roof of the leachate treatment facility (P7), the rest two points were arranged on the north of biofilter (P5, P6). Overall, 8 sampling points were arranged in the plant outside of the facilities (Fig. 1). The sampling campaign was conducted on May 10th 2013 and lasted from 8:00 to 19:00 (Noted: The operation time in the plant was from 7:00 to 13:00). Sampling in each point were respectively at 9:00, 12:00 and 17:00, totally 24 samples.

2.2 Gas sampling and analyses

Four methods were used to measure different gaseous pollutants in this study, 1) colorimetric tubes, 2) gas-chromatography (GC) with mass spectrometry (GC-MS) or flame ionization detection (GC-FID) or pulsed flame photometric detection (GC-PFPD) preceded by cold trap concentration, 3) GC-FID preceded by sorbent concentration, and 4) high-performance liquid chromatography (HPLC) after derivation by 2,4-dinitrophenylhydrazine (DNPH).

2.2.1 GC analysis after cold pre-concentration

Samples were grabbed using Tedlar bags from the air. Tedlar bag was placed in a vacuum-generating container. Using a vacuum pump connected to the container, the samples were drawn directly into the Tedlar bags via Teflon tube. These samples were then transported immediately to the lab for analysis (within 24 hours) to minimize the loss of reduced sulfur compounds (RSC) during storage.

Ambient air samples were pre-concentrated by cryogenic liquid nitrogen according to the EPA TO15 method. The pre-concentration instrument used was an Entech 7100A (Entech Instruments Inc., USA) and the injection volume was 50-500 mL.

Conditions for GC-PFPD and GC-FID had been reported by Fang et al. (2012, 2013)

2.2.2 GC-FID analysis after sorbent concentration

The sorbent concentration method was used to determine volatile fatty acids (VFAs) in the air samples. Commercial sorbent tubes (Silica Gel Tube, SKC, USA) were used to collect the air samples. The air flow rate was 1000 mL/min and the collection time was 120 min. After sampling, the tube were capped with the end plugs and transported back to lab for analysis. The silica gel was placed into 5 mL volumetric flask and was desorbed by 5 mL of deionized water. After standing 30 min in the ultrasonic

instrument, the supernate of the liquid were analyzed by GC-FID. The operation parameters for the FID detection system were the same as described above.

2.2.3 HPLC analysis after derivation by DNPH

EPA method TO11A was applied to determine aldehydes in the air samples.

Commercial cartridges (Cleanert DNPH-Silica, Agela Technology, China) were used to collect the air samples. The air flow rate was 1000 mL/min and the collection time was 30 min. After sampling, the cartridges were connected to a clean syringe (Visiprep DL, Supelco Analytical, USA) and placed on the solid phase extraction vacuum manifold (Visiprep, Supelco Analytical, USA), after which compounds absorbed onto the cartridges were eluted into a 5 mL volumetric flask with 5 mL of acetonitrile.

The analytical column used was a C18 (4.6 mm ID × 25 cm, 5 μm) stainless steel tube (Venusil XBP, Agela Technology, China) and the mobile phase was acetonitrile (Merck, Germany) and high purity water (Milli-Q Millipore, USA). The elution program was 45% acetonitrile for 1 min, followed by a linear gradient from 45% to 75% acetonitrile in 30 min, which was then held for 5 min. The flow rate was 2 mL/min and the sample injection volume was 25 μL. The detection limit of this method was 50 ppb.

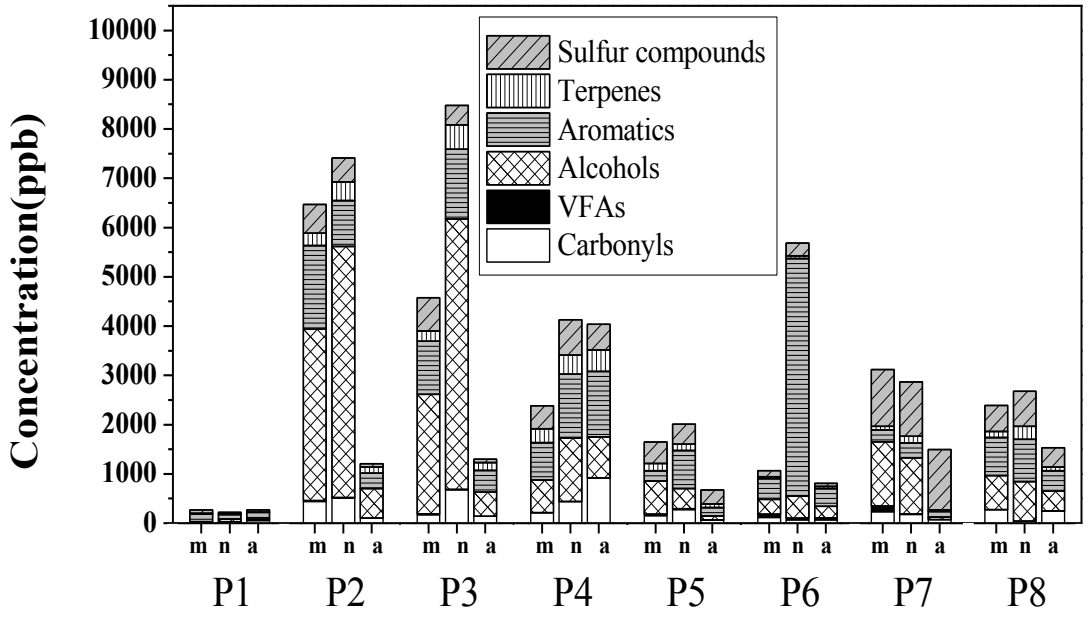

Figure 2: Total concentration and composition of the odour compounds in the 8 points. In X-axis, "m", represents 9:00, "n", represents 12:00, "a", represents 17:00.

3. Results and discussion

Six groups of pollutants including sulfur compounds, carbonyls, alcohols, aromatics, alkanes, alkenes, terpenes and VFAs were identified. The concentrations of the gaseous pollutants in the air at the 8 sampling points are shown in Fig. 2.

Carbonyls including ketones and aldehydes, and the dominant carbonyls in this plant were butyraldehyde and crotonaldehyde, as shown in Fig. 3(b). VFAs were almost below 50 ppb except P6 and P7, where the concentrations were higher than other

places and above this value, as shown in Fig. 3(c). Alcohols showed an extra high value in the biofilter exhaust pipe, and mainly was ethanol from the Fig. 3(d). Ethanol showed a great decrease in the afternoon, from 4745 ppb declining to 521 ppb in P2 and from 5342 ppb declining to 453 ppb in P3. The relatively higher concentrations of ethanol could be due to the anaerobic conditions of the materials.

Six representative aromatics were identified in this study, as shown in Fig. 3(e). Except for P6, the concentrations of the other places were below 2000 ppb. Some researchers have reported that aromatics originated from the decomposition of plastics and solvents (Pierucci et al., 2005), while others suggested that they were xenobiotic compounds disseminated from raw materials, rather than intermediate products of waste biodegradation (Komilis et al., 2004). Aromatics can also be found in the gaseous contaminants of sludge degradation (Huang et al., 2011). The dominant compounds of this family were not obvious.

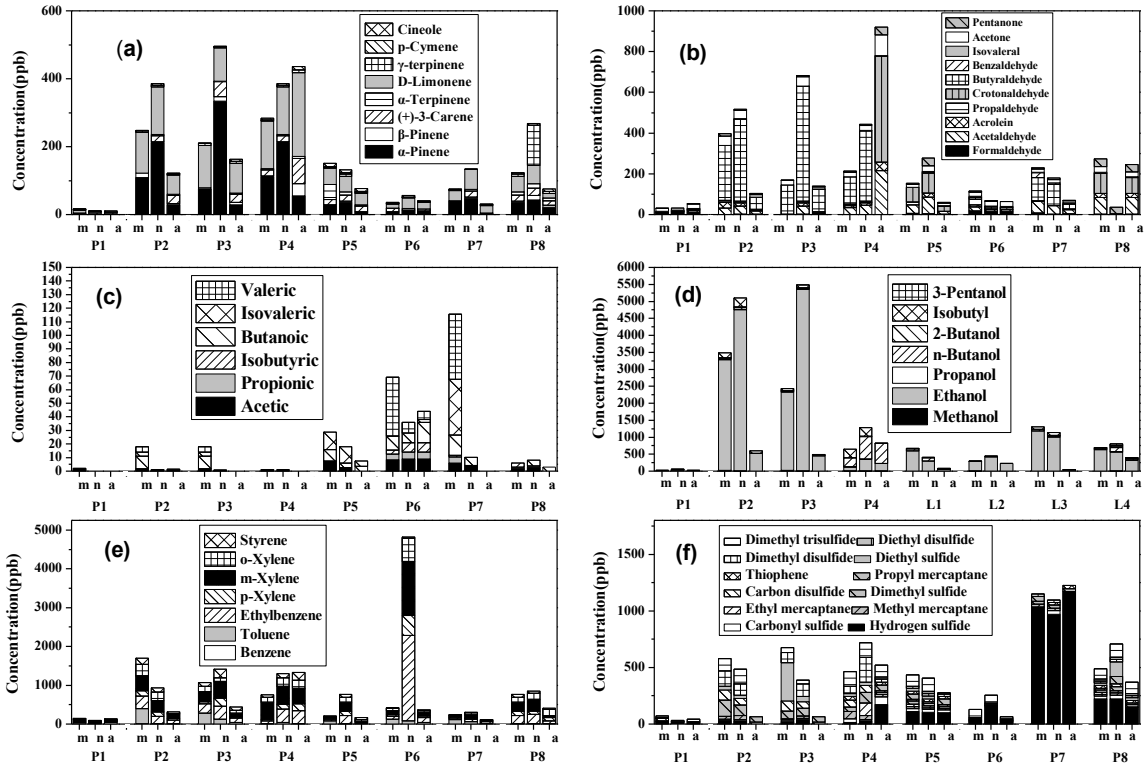

Figure 3: Composition of each odour family and concentration of each compound in the plant. (a) Terpenes, (b) Carbonyls, (c) VFAs, (d) Alcohols (e) Aromatics, (f) Sulfur compounds. In X-axis, "m" represented 9:00, "n" represented 12:00, "a" represented 17:00.

Sulfur compounds showed strong relationships with the physicochemical properties of the waste. In this plant, the characteristics of sulfur compounds composition could be discriminated into two groups. One was more similar in P2, P3 and P4, where the proportion of hydrogen sulfide was low, while the other group was more similar in P5, P6, P7 and P8, where the proportion of hydrogen sulfide was relatively high. Cysteine and methtonine were two kinds of amino acids in proteins that contain sulfur. Decomposition of organic sulfur under oxic (presence of oxygen) conditions resulted in mecaptans (Organic group - SH) and anoxic conditions (absence of oxygen) resulted in

hydrogen sulfide. Both these products were generated when biodecomposition occurs. In addition, dimethyl sulfide was generated under conditions of anoxic circumstances predominate. Hydrogen sulfide occurred largely only when the pH and oxygen concentration of the waste reduced and in this case the high proportion of hydrogen sulfide were most probably caused by the anaerobic tank of leachate treatment facility. Due to the low odour threshold value of hydrogen sulfide, the odour impact of leachate treatment facility to the neighbourhood circumstance was much larger than the biofilters and the waste treatment facilities.

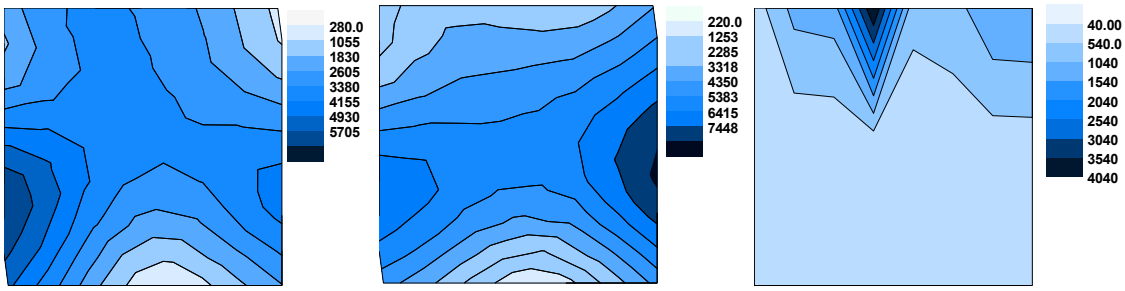

Figure 4: Contour figures of the total pollutants in different times in the plant. (a) At 9:00, (b) At 12:00, (c) At 17:00. The unit of the contour data is ppb.

The contour figures were got through the total concentration and the coordinate of each point, as shown in Fig. 4. From the figure, the distributions of odour pollutants in the plant were very similar in the morning and at noon, in which the biofilter exhaust pipe was the major source to the surrounding circumstance. Nevertheless, the leachate treatment facility became the major source in the afternoon, in which the waste treatment was ceased and the running of biofilter was stopped.

4. Conclusions

The odour concentration at noon in this plant was much higher than that in other times. The concentration fluctuation law in these places was more influenced by the operation time of the treatment plant. The main contributors to malodorous smell were carbonyls, alcohols and sulfur compounds, mainly butyraldehyde, crotonaldehyde, ethanol and hydrogen sulfide. The odour impact of leachate treatment facility to the neighbourhood circumstance was much larger than the biofilters and waste treatment facilities.

Acknowledgements

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References

Bockreis A., Steinberg I. 2005. Measurement of odour with focus on sampling techniques. Waste Management 25:859-863.

Cadena E., Colon J., A.Sanchez, X. Font, Artola A. 2009. A methodology to determine gaseous emissions in a composting plant. Waste Management 29:2799-2807.

Calabro, P.S., Moraci N., Orsi S., Gentili E. The effect of mechanical-biological pretreatment of municipal waste on a landfill management. In: Proceeding of Eleventh International Waste Management and Landfill Symposium. Sardinia, Cagliari, Italy, October 1-5, 2007.

Clemens, J., Cuhls C. 2003. Greenhouse gas emissions from mechanical and biological waste treatment of municipal waste. Environmental Technology 24:745-754.

Domingo, J.L., Nadal M. 2009. Domestic waste composting facilities: a review of human health risks. Environment International 35:382-389.

Eitzer, B.D. 1995. Emissions of volatile organic chemicals from municipal solid waste composting facilities. Environmental Science Technology 29:896-902.

Huang, L.K., Wang G.Z., Zuo J.L. 2011.Species of volatile organic compounds from municipal wastewater treatment plant. Environmental Biotechnology and Materials Engineering183:1057-1060.

Fang J.J., Yang N., Cen D.Y., Shao L.M., He P.J. 2012. Odor compounds from different sources of landfill: Characterization and source identification. Waste Management, 32: 1401-1410.

Fang J. J., Zhang H., Yang N., Shao L.M., He P.J. 2013. Gaseous pollutants emitted from a mechanical biological treatment plant for municipal solid waste: Odor assessment and photochemical reactivity. Journal of the Air & Waste Management Association, 63(11): 1287–1297.

Karageorgos, P., Latos M., Kotsifaki C. 2005. Treatment of unpleasant odors in municipal wastewater treatment plants. Water Science and Technology 61:2635-2644.

Komilis, D.P., Ham R.K., Park J.K. 2004. Emission of volatile organic compounds during composting of municipal solid wastes. Water Research 38:1707-1714.

Staley, B.F., Xu F.X., Cowie S.J., Barlaz M.A., Hater G.R. 2006. Release of trace organic compounds during the decomposition of municipal solid waste components. Environmental Science & Technology 40:5984-5991.

Mao, I.F., Tsai C.J., Shen S.H., Lin T.F., Chen W.K., Chen M.L. 2006. Critical components of odors in evaluating the performance of food waste composting plants. Science of the Total Environment 370:323-329.

Nicolas, J., Romain A.C., Ledent C. 2006. The electronic nose as a warning device of the odour emergence in a compost hall, Sensors and Actuators B: Chemical 116:95-99

Norbu,T., Visvanathan C., Basnayake B. 2005. Pretreatment of municipal solid waste prior to landfilling. Waste Management 25:997-1003.

Pierucci, P., Porazzi E., Martinez M.P., Adani F., Carati C., Rubino F.M., Colombi A., Calcaterra E., Benfenati E. 2005.Volatile organic compounds produced during the aerobic biological processing of municipal solid waste in a pilot plant. Chemosphere 59:423-430.

Rodriguez, M.D., Montoya R.M., Giraldez I., Cabeza I.O., López R., Díaz M.J. 2010. Effect of control parameters on emitted volatile compounds in municipal solid waste and pine trimmings composting. Journal of Environmental Science and Health, Part A—Toxic/Hazardous Substances & Environmental Engineering 45:855-862.

Thriel,C.V., Schaper M., Kiesswetter E., Kleinbeck S., Juran S., Blaszkewicz M., Fricke H.H., Altmann L., Berresheim H., Bruning T. 2006. From chemosensory thresholds to whole body exposures-experimental approaches evaluating chemosensory effects of chemicals. International Archives of Occupational and Environmental Health 79:308-321.

Tolvanen, O., Nykanen J., Nivukoski U., Himanen M., Veijanen A., Hanninen K. 2005. Occupational hygiene in a Finnish drum composting plant. Waste Management 25:427-433.

Tränkler, J., Visvanathan C., Kurupan P. 2005. Mechanical-biological waste treatment -the southeast Asian experiences. In: Proceedings of Tenth International Waste Management and Landfill Symposium. Sardinia 2005, Cagliari, Italy, 3–7 October.

Tsai, C.J., Chen M.L., Ye A.D., Chou M.S., Shen S.H., Mao I.F. 2008. The relationship of odor concentration and the critical components emitted from food waste composting plants. Atmospheric Environment 42:8246-8251.

Assessment of odour activity value coefficient and odour contribution based on binary interaction effects in a waste disposal plant

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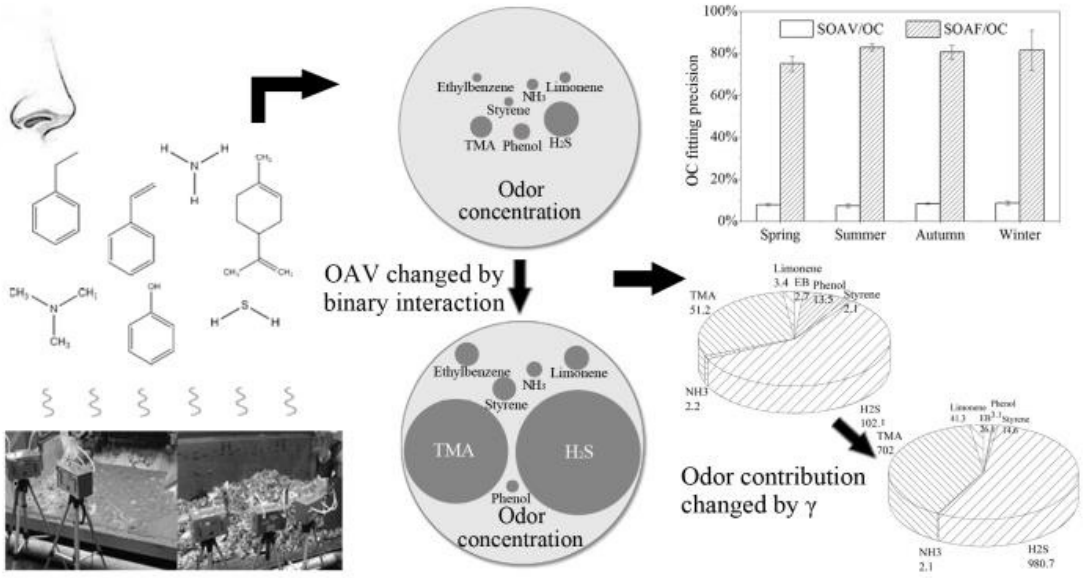
Graphical Abstract



The odour activity value (OAV) has been widely used for the assessment of odour pollution from various sources. However, little attention has been paid to the extreme OAV variation and potential inaccuracies of odour contribution assessment caused by odour interaction effects. In our recent studies (Wu et al., 2015), an odour activity value coefficient (γ) was first proposed to evaluate the type and the level of binary interaction effects based on the determination of OAV variation in the binary odorous mixture. By multiplying OAV and γ, the odour activity factor (OAF) was used to reflect the real OAV. The correlation between the sum of OAF and odour concentration reached 80.0 ± 5.7%, which was 10 times higher than the sum of OAV used before. Results showed that hydrogen sulfide contributed most (annual average 66.4 ± 15.8%) to odour pollution in the waste disposal plant. However, as the odour intensity of samples in summer is rising, the odour contribution of trimethylamine was improved to 48.3 ± 3.7% by the synergistic interaction effect, which was not found in previous studies.

1. Introduction

Recently, the emission of odorants has attracted enormous attention due to their harmful effects on human health and atmospheric environment (Qin et al., 2013) . Odour activity value (OAV) has been widely used for the assessment of odour pollution

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from various sources. However, applying OAV in the assessment of odour contribution is valid only under the hypothesis that interaction effects between components can be ignored (Feilberg et al., 2010, Hales et al., 2012). Indeed, odorants in mixtures have shown complex interaction effects, such as additive, antagonistic and synergistic interaction (Yan et al., 2014). These interaction effects lead to extreme OAV variation and potential inaccuracy in the assessment of individual odour contribution. Yet studies concerning the evaluation of odour interaction effects and the revise of OAV variation are limited. Therefore, a proper method is still needed to evaluate these interaction effects in odorous mixture.

2. Materials and methods

Air sample in the food waste disposal plant was collected by a 5 L Tedlar sampling bag (SKC Inc., USA). Analytical methods for the determination of various components in air samples were based on a pre-concentration step followed by the subsequent separation and detection by a gas chromatography/mass spectrometry and gas chromatography/ flame photometric detector.
Odour concentration (OC), odour intensity (OI) and odour threshold value (OTV) were measured with dynamic olfactometry (AC'SCENT, USA) by sniffing panelists. Then OAV was calculated as the ratio of the concentration to the OTV of each odorant.
γ was measured in an odorless laboratory. A determined odorant and the reference odorant were mixed, volatilized and diluted by pure air in a Tedlar bag. Concentrations were adjusted to make the determined odorant and the reference odorant to reach same OI value, namely, form isointense mixture. In this instance, the ratio of OAV_{Pure} to OAV_{Mixed} was defined as γ (OAV_{Pure} was OAV of the single determined odorant, and OAV_{Mixed} was OAV of the determined odorant in isointense mixture) (Wu et al., 2015).

3. Results and discussion

A total of 28 odorants were detected, and the average concentration of each category was in the following order: Aromatics (919.4 μg m^{-3}) > Terpene (757.0 μg m^{-3}) > Nitrogenous compounds (607.9 μg m^{-3}) > Oxygenated compounds (305.6 μg m^{-3}) > Halogenated compounds (92.0 μg m^{-3}) > Alkanes (72.7 μg m^{-3}) > RSCs (53.0 μg m^{-3}).
Mean OAV of odorants with detectable frequency higher than 50% were calculated in this study. On the basis of Chen (Chen et al., 2000) and Parker's (Parker et al., 2012) theory, odorants with detectable frequency over 50% and OAV above 1 were defined as key odorants in this study, including hydrogen sulfide, trimethylamine, phenol, limonene, ethylbenzene, styrene and ammonia. The sum of the seven key odorants' mean OAV was 177.2, which was far less than average OC (2183 ± 1692 ou m^{-3}). Therefore, a proper method is needed to evaluate odour interaction effects precisely.
Hydrogen sulfide was selected as reference odorant for its highest OAV and distinct odour characterization, and binary interaction effects between key odorant and the reference odorant were assessed to optimize the evaluation of odour interaction effects in this study. Based on the study of OAV-OI relationship of single odorants and odorants in isointense mixture with hydrogen sulfide, the functional formula relating γ with OI was concluded as $lg\ \gamma = k' OI_{Mixture} + b'$.
The ratio of OAV_{Pure} to OAV_{Mixed} reflects the change of odorous ability caused by binary interaction effects, so γ might quantitatively characterize the type and the level of binary interaction effects. Previous researchers had also reported similar odour interaction effects in binary mixtures. These results were meaningful for binary interaction effects studies but limited to a given mixing proportion in controlled

laboratory experiment. By proposing the odour activity value coefficient in our study, we expect quantitatively evaluating the type and the level of binary interaction effects in odour samples from various odour sources. OAF stands for the real OAV which is taking binary interaction effects into consideration.

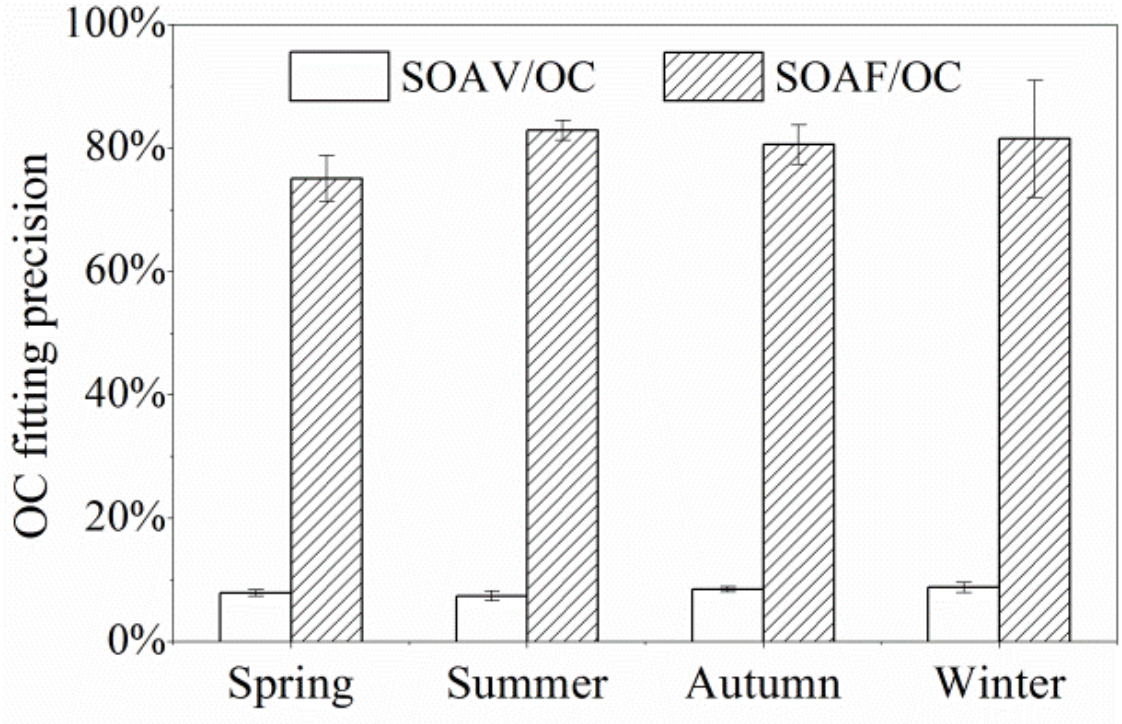

Figure 1: Comparison of SOAV, SOAF and OC of odour samples in each season. SOAV: the sum of odour activity value, SOAF: the sum of odour activity factor, OC: odour concentration determined by dynamic olfactometry. Error bars indicate disparity of odour emission at each sampling site (Wu et al., 2015).

Fig. 1 reflects the comparison of mean SOAV, SOAF and OC of odour samples collected at four sites in each season. On average, SOAF matched 80.0% ± 5.7% of OC. It was 10 times higher than SOAV which was widely used in previous assessments of odour contribution. The average odour contribution of key odorants in each season was reflected in Fig. 2. Generally, hydrogen sulfide was the largest contributor (annual average 66.4 ± 15.8%) to odour pollution in the waste disposal plant. However, as OI of odour samples in summer were rising, the odour contribution of trimethylamine was improved to 48.3 ± 3.7% by the increasing synergistic interaction effect, while odour contribution of phenol decreased to 0.1 ± 0.02% for the increasing antagonistic effect.

4. Conclusions

This study showed a novel odour activity value coefficient method for the assessment of binary interaction effects. The correlation between SOAF and OC was about 10 times higher than that of SOAV, and odour contribution of trimethylamine in summer was improved to 48.3 ± 3.7% by the synergistic interaction effect, which was not found in previous studies. This might be useful for precise prediction and effective treatment of odour pollution in various regions.

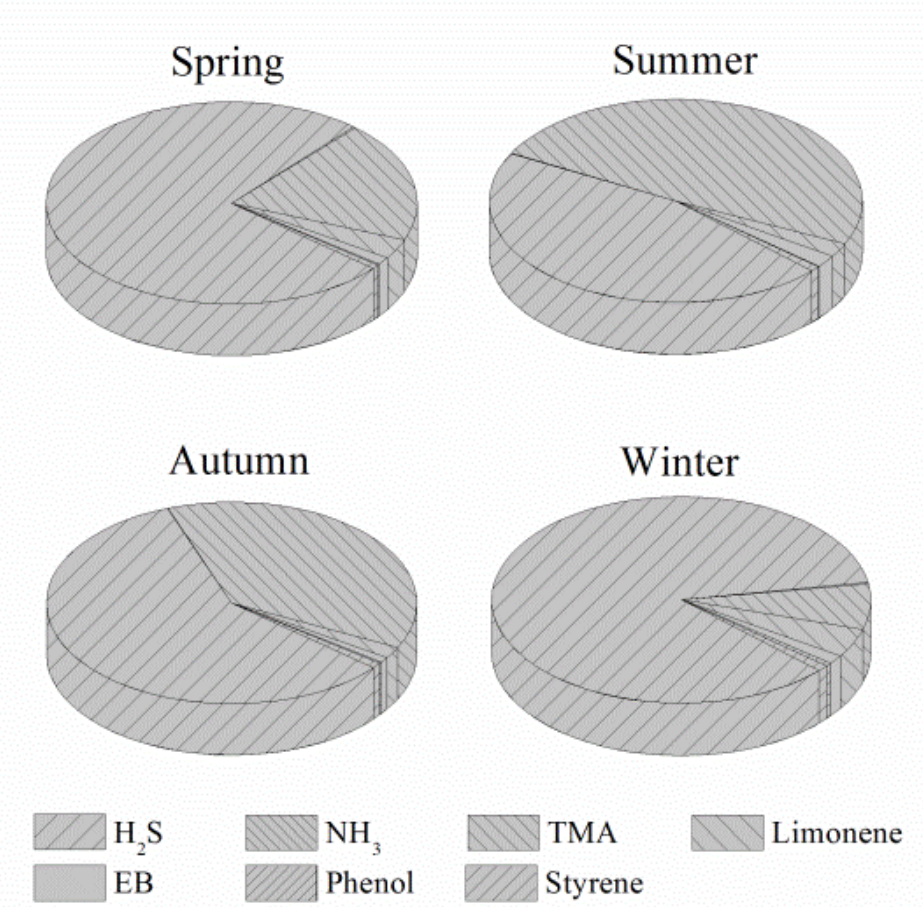

Figure 2: Average odour contribution of key odorants in each season. EB: ethylbenzene, H_2S: hydrogen sulfide, NH_3: ammonia, TMA: trimethylamine (Wu et al., 2015).

References

Chen, L. Y., Jeng, P. T., Chang, M. W. & Yen, S. H. 2000. Rationalization of an odor monitoring system: A case study of Lin-Yuan Petrochemical Park. Environmental Science & Technology, 34**,** 1166-1173.

Feilberg, A., Liu, D., Adamsen, A. P., Hansen, M. J. & Jonassen, K. E. 2010. Odorant emissions from intensive pig production measured by online proton-transfer-reaction mass spectrometry. Environmental science & technology, 44**,** 5894-5900.

Hales, K. E., Parker, D. B. & Cole, N. A. 2012. Potential odorous volatile organic compound emissions from feces and urine from cattle fed corn-based diets with wet distillers grains and solubles. Atmospheric environment, 60**,** 292-297.

Parker, D. B., Koziel, J. A., Cai, L., Jacobson, L. D., Akdeniz, N., Bereznicki, S. D., Lim, T. T., Caraway, E. A., Zhang, S., Hoff, S. J., Heber, A. J., Heathcote, K. Y. & Hetchler, B. P. 2012. Odor and Odorous Chemical Emissions from Animal Buildings: Part 6. Odor Activity Value. Transactions of the Asabe, 55**,** 2357-2368.

Qin, Y., Liu, J., Wang, G. & Zhang, Y. 2013. Evaluation of indoor air quality based on qualitative, quantitative and olfactory analysis. Chinese Science Bulletin, 58**,** 986-991.

Wu, C., Liu, J., Yan, L., Chen, H., Shao, H. & Meng, T. 2015. Assessment of odor activity value coefficient and odor contribution based on binary interaction effects in waste disposal plant. Atmospheric Environment, 103**,** 231-237.

Yan, L., Liu, J., Wang, G. & Wu, C. 2014. An Odor Interaction Model of Binary Odorant Mixtures by a Partial Differential Equation Method. Sensors, 14**,** 12256-12270.

Mapping odour sources with a mobile robot in a time variant airflow environment

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This paper focuses on the problem of mapping odour sources using a mobile robot in a time-variant airflow environment, and provides a localization method which uses the Dempster-Shafer (D-S) theory to reason the possible locations of odour sources. In the proposed method, the robot carries out the D-S inference and iteratively updates a grid map, using the successive measurements from a gas sensor and an anemometer when the robot is cruising in the given search area. Simulations are carried out and the results in a time-variant airflow environment show that the locations of the multiple odour sources can be estimated online with the proposed method.

1. Introduction

Odour information is widely used by many animals for searching for food, finding mates, exchanging information, and evading predators. Inspired by the olfaction abilities of many animals, in the early 1990s, people started to try building mobile robots with similar olfaction abilities to replace trained animals (Sandini and Lucarini et al., 1993; Consi and Atema et al., 1994; Ishida and Suetsugu et al., 1994; Russell and Thiel et al., 1994). It is expected that mobile robots developed with such olfaction capability will play more and more roles in such areas as judging toxic or harmful gas leakage location, checking for contraband (e.g., heroin), searching for survivors in collapsed buildings, humanitarian de-mining, and antiterrorist attacks.

The methods of odour source localization (OSL) realized using an individual or multiple mobile robots can be classified into tracing-behavior-based methods and analytical-model-based methods (Lilienthal and Loutfi et al., 2006). In the tracing-behavior-based group, the source location is often determined by the final position of the mobile robot doing plume tracing and successfully arriving at the source. An alternate name for OSL, chemical plume tracing (Farrell and Pang et al., 2005; Zarzhitsky and Spears et al., 2005), reflects the importance of the plume-tracing strategy in these methods. Some biologically inspired approaches have been designed for mobile robot based plume tracing, such as gradient-following-based algorithm in low Reynolds number (Berg, 1990) and up-wind algorithm in a wind tunnel (Belanger and Willis, 1996), which intended to mimic the behaviors of chemotaxis and anemotaxis of a few biological entities, respectively. Moreover, some engineered plume tracing strategies have also been proposed, such as fluxotaxis (Zarzhitsky and Spears et al., 2005) and infotaxis (Vergassola and Villermaux et al., 2007) algorithms. A combination of the biomimetic and engineered strategies can be found in (Li and Farrell et al., 2006).

Comparatively, only a few analytical-model-based methods have been reported, such as modeling the wind field using naive physics (Kowadlo and Russell, 2006; Kowadlo and Russell, 2009), remote gas source localization (Ishida and Nakamoto et al., 1998),

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building gas distribution grid maps (Lilienthal and Duckett, 2004), a source-likelihood mapping approach based on the Bayesian inference method (Pang and Farrell, 2006), mapping multiple odour sources using Bayesian occupancy grid map (Ferri and Jakuba et al., 2011), and localizing via Particle Filter (Li and Meng et al., 2011) in our earlier work, etc. Kowadlo et al. (Kowadlo and Russell, 2006; Kowadlo and Russell, 2009) tried to obtain the location of the odour source by mapping the search area in environments with a stable airflow field. Ishida et al. (Ishida and Nakamoto et al., 1998) intended to identify the source location based on a time-averaged gas distribution model in conditions with stable airflows and stable odour release rate. Lilienthal et al. (Lilienthal and Duckett, 2004) demonstrated that the position of the average maximum concentration can often be used to estimate the source location in environments with no strong airflow. Pang et al. (Pang and Farrell, 2006) localized the odour source offline using Bayesian inference in near-shore ocean conditions with an autonomous underwater vehicle. Ferri, G., et al. (Ferri and Jakuba et al., 2011) located multiple odour sources by a Bayesian occupancy grid mapping based method in an uncontrolled indoor environment. In our earlier work (Li and Meng et al., 2011), a PF-based OSL algorithm was presented to localize an odour source in outdoor airflow environments.

For tracing-behavior-based methods, it is difficult for the robot to automatically provide the source location with its final position because the robot cannot know whether it arrives at the source. Therefore, to automatically obtain the source location by the robot itself, an analytical-model-based method is necessary. However, the methods proposed in (Kowadlo and Russell, 2006; Kowadlo and Russell, 2009) and (Ferri and Jakuba et al., 2011) might not work in real outdoor environments because the required conditions, i.e., stable airflow field or weak airflow, are hardly satisfied in outdoor environments where the airflow is almost always turbulent, time varying, and strong. And the methods presented in (Pang and Farrell, 2006) and (Li and Meng et al., 2011) only suit the cases with a single odour source. Unfortunately, large amount of OSL problems not only happen in environments with turbulent flow, but also involve multiple odour sources.

This paper presents a multiple odour sources localization (MOSL) method via D-S inference to estimate the locations of the odour sources while the robot performs exploratory behavior in an outdoor environment with time-variant airflow. The purpose of the exploratory behavior is to collect information associated with the locations of the odour source, such as odour concentrations and airflow directions/velocities, and the collected information is exploited by the D-S Inference to obtain the solution to the MOSL problem. In current study, the exploratory behavior of the robot is by following a predefined path shaped like rectangular wave to cover the given search region. To exploit the collected information, belief mass functions is constructed and used in the proposed MOSL algorithm, even though the belief mass functions are sometimes inaccurate.

The remainder of this paper is organized as follows. Section 2 introduces the D-S inference for MOSL. The belief mass function for MOSL is presented in section 3, and the simulation setup and results are presented in section 4. The conclude is presented in the final section.

2. D-S Inference for MOSL

2.1 Introduction of D-S Theory

D-S theory has established itself as a promising and popular approach to data fusion especially in the last few years (Khaleghi and Khamis et al., 2013). It can be considered as a generalization to the Bayesian theory that deals with probability mass functions. Unlike the Bayesian Inference, the D–S theory allows each source to contribute information in different levels of detail. Furthermore, D–S theory does not assign a priori probabilities to unknown propositions; instead probabilities are assigned only when the supporting information is available. In fact, it allows for explicit representation of total ignorance by assigning the entire mass to the frame of discernment at any time, whereas using probability theory one has to assume a uniform distribution to deal with this situation.

Consider Θ to represent all possible states of the frame of discernment and the power set 2^{Θ} to represent the set of all possible subsets of Θ. In contrast to probability theory that assigns a probability mass to each element of Θ, D–S theory assigns belief mass m to each element e of 2^{Θ}, which represent possible propositions regarding the system state. Function m has two properties: $m(\phi) = 0$ and $\sum_{e \subseteq 2^{\Theta}} m(e) = 1$.

2.2 MOSL using D-S Inference

In most OSL applications, the odour sources are immovable, thus the distribution of the odour sources can be conveniently represented by a grid map $\{C_i, i = 1,2,\cdots M\}$, where the constant M is the number of the cells in the grid map. For each cell C_i in the grid map, it has two states, named S (occupied by an odour source), $\overline{S}$ (not occupied by odour source), respectively, composing a frame of discernment $\Theta = \{S, \overline{S}\}$.

Intuitively for any proposition e, $m(e)$ represents the proportion of available evidence that supports the claim that the actual cell state belongs to e. When the robot takes a measurement, there will be a piece of evidence. Given two pieces of evidence with corresponding belief mass functions $m_1(e_1)$ and $m_2(e_2)$, $e_1, e_2 \in 2^{\Theta}$ (to be detailed in section 3), using the Dempster's rule of combination, the two pieces of evidence can be fused and produce a joint belief mass function $m_{1,2}(e)$ as (Shafer, 1976)

$$m_{1,2}(e) = (m_1 \oplus m_2)(e) = \sum_{e_1 \cap e_2 = e \neq \phi} m_1(e_1) m_2(e_2) / (1 - K), \tag{1}$$

where K represents the amount of conflict between the two evidences and is given by

$$K = \sum_{e_1 \cap e_2 = \phi} m_1(e_1) m_2(e_2). \tag{2}$$

It is not hard to find that the power set 2^{Θ} only has four elements, ϕ, $\{S\}$, $\{\overline{S}\}$, and $\{S, \overline{S}\}$ (i.e., Θ). In order to understand easily, here we denote the subset $\{S, \overline{S}\}$ as U (unknown). Thus, there is

$$m(S) + m(\overline{S}) + m(U) = 1 \quad . \tag{3}$$

Since the frame of discernment $\Theta = \{S, \overline{S}\}$ only has two states, the proposed D-S inference for MOSL itself is simple and will not suffer the exponential complexity of computations. In addition, because the Dempster's rule of combination satisfies the

associative law, i.e., $m_1 \oplus m_2 \oplus m_3 = (m_1 \oplus m_2) \oplus m_3 = m_1 \oplus (m_2 \oplus m_3)$, thus there is $m_1 \oplus m_2 \oplus \cdots \oplus m_n = (m_1 \oplus m_2 \oplus \cdots \oplus m_{n-1}) \oplus m_n$, and we can easily perform a recursively inference using new coming evidence from the successive measurements by the robot.

3. Belief Mass Function for MOSL

In our earlier work, we use item "odor-patch path" to represent the trajectory that the concerned odour patch passed by. In fact, odour patches are imaged air mass which contains enough odour molecules. Not only are there air masses containing enough odour molecules, but also air masses without enough odour molecules or even having no odour molecule. When robot encounters the former, an odour detection event would be happen, the latter a non-detection event. Because both the detection and non-detection events will be helpful to localize the odour source, so we might as well use a new item "air-mass path" which is defined as the trajectory most likely taken by an air mass encountered with the mobile robot.

Same as the estimation of odor-patch path in our earlier work, we can get an estimation of air-mass path. Intuitively, if we get a detection event, there will likely be one or some odour sources in the area covered by the estimated air-mass path. Otherwise, the possibility there are some odour sources in the covered region will decrease.

Let the set $\{\pi_i, i = 1,2,\cdots M\}$ denote the probability map of the air-mass path that has been estimated in (Li and Yang et al., 2013), where π_i indicates the probability that the air mass arrived at the robot comes from the cell C_i, and the constant M is the number of the cells in the grid map. Therefore, the belief mass function can be given for both detection event D and non-detection event $\overline{D}$ respectively as follows:

$$m(e)|_i^D = \begin{cases} \mu_D \xi \pi_i & e = S \\ 0 & e = \overline{S} \\ 1 - \mu_D \xi \pi_i & e = U \end{cases}, \tag{4-a}$$

$$m(e)|_i^{\overline{D}} = \begin{cases} 0 & e = S \\ \mu_{\overline{D}} \xi \rho \pi_i & e = \overline{S} \\ 1 - \mu_{\overline{D}} \xi \rho \pi_i & e = U \end{cases}, \tag{4-b}$$

where μ_D is the probability of detection event D arising given that there is detectable odour at the position of the robot; $\mu_{\overline{D}}$ is the probability of non-detection event $\overline{D}$ happening given that there is no detectable odour at the position of the robot; ξ represents the reliability of the model of the air mass transportation (detailed in section 4.1); ρ indicates the reliability decreasing because of the intermittency of the odour plume or the lack of enough odour molecules (easily cause the false non-detection event).

According to our test data of the gas sensor, $\mu_D \approx 0.9$, $\mu_{\overline{D}} \approx 1.0$; ξ and ρ vary with the distance from a location to the robot, and we conservatively choose $\xi \approx 0.6$ and $\rho = 0.5$ in this research.

4. Simulations

4.1 Simulation Platform Setup

In our research, in order to have a repeatable and controllable flow-field and plume, and also to reduce the computational load, a flow-field file with frame structure, just like a movie, is generated from the simulation platform released by Jay A. Farrell and his colleagues (Farrell and Murlis et al., 2002). The file has a constant time interval 0.5s between consecutive frames, and each frame contains the flow information with 15×15 grids as well as the positions and concentrations of all odour puffs. All data in a frame was intercepted and saved during the running of the Farrell's simulation platform without any modification. In this research, the code of the simulation platform (Farrell and Murlis et al., 2002) was modified to have several odour sources.

On our simulation experiment platform, the flow-field file is replayed just as same as the play on the Farrell's simulation platform, but almost without any calculation because the calculation has been done on the Farrell's platform when the file was being generated.

4.2 Simulations and Results

In this study, the robot simply follows a predefined path shaped like rectangular wave to cover the given search region, performing an exploratory behavior. At each time step, the robot collects the odour concentration, airflow speed and direction by the equipped gas sensor and the anemometer, respectively.

Fig. 1 illustrates four scenes of the estimated distribution of the two odour source, in which the virtual robot can achieve a maximum speed of 0.5 m/s, the mean flow velocity is about 1.0 m/s and the mean flow direction is about 0°. The two odour sources locate at (20.0m, 50.0m) and (24.0m, 55.0m), with same area 0.3m×0.3m. The robot starts at the location (33.0m, 40.0m) to search a given rectangular region with left-top corner (18.7m, 60.3m) and right-bottom corner (32.7m, 40.3m). It firstly goes vertically up to the top bound of the given region, and then goes vertically down to the bottom bound with an fixed offset 2m in left direction (called 1 return, see Fig. 1(a)), and so on. When the robot arrives at the left-top corner (called 1 round, see Fig. 1(c)), the robot comes back to the right-bottom corner, and starts a new round of the exploration, and so on.

It can be found from Fig. 1 that, the distribution map of the two odour sources is updated recursively via the proposed D-S inference using new coming evidence from the successive measurements by the robot when the robot is cruising in the given search area. Apparently, the estimated locations of the two odour sources approach to the true sites as the evidence accumulates.

It also can be found that in Fig. 1(d), near the right bound of the search region, there are still some cells with false information of being occupied by an odour source. This is because that, the mean airflow direction is about 0° in this simulation, and the robot often has detection events near the right bound, resulting some cells with confusing information. This result suggests that more exploration should be performed to the region near these cells.

5. Conclusion

In this research, the robot carries out the proposed D-S inference and iteratively updates a grid map indicating the possible locations of two odour sources, using the

successive measurements from a gas sensor and an anemometer when the robot performs an exploration in the given region. Simulations are carried out and the results in a time-variant airflow environment show that the locations of the multiple odour sources can be estimated and approach to the true sites as the evidence accumulates. The simulations also indicate that the proposed method has a low computational cost which allows it to be used in online applications.

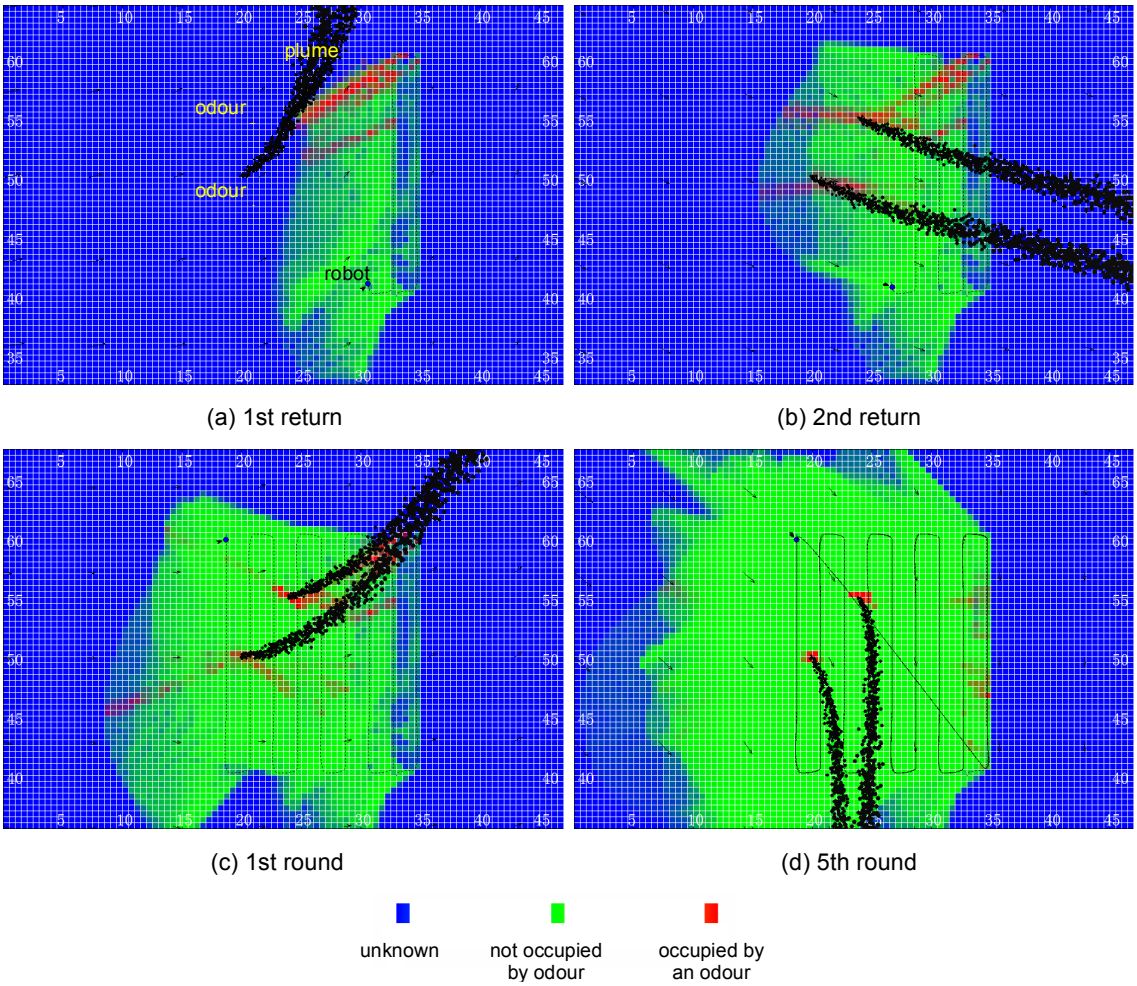

Figure 1: Estimated distribution map of two odour sources at different time via the proposed D-S inference algorithm.

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References

Belanger, J. H. and M. A. Willis (1996). "Adaptive control of odor-guided locomotion: behavioral flexibility as an antidote to environmental unpredictability." Adaptive Behavior 4(3-4): 217-253.

Berg, H. C. (1990). Bacterial microprocessing. Proceedings of Cold Springs Harbor Symp, Quantum Biology.

Consi, T. R. and J. Atema, et al. (1994). AUV guidance with chemical signals. Proceedings of IEEE Sympsium on Autonomous Underwater Vehicle Technology, Cambridge, MA, USA, IEEE.

Farrell, J. A. and J. Murlis, et al. (2002). "Filament-based atmospheric dispersion model to achieve short time-scale structure of odor plumes." Environmental Fluid Mechanics 2(1): 143-169.

Farrell, J. A. and S. Pang, et al. (2005). "Chemical plume tracing via an autonomous underwater vehicle." IEEE Journal of Oceanic Engineering 30(2): 428-442.

Ferri, G. and M. V. Jakuba, et al. (2011). "Mapping multiple gas/odor sources in an uncontrolled indoor environment using a Bayesian occupancy grid mapping based method." Robotics and Autonomous Systems 11(59): 988–1000.

Ishida, H. and K. Suetsugu, et al. (1994). "Study of autonomous mobile sensing system for localization of odor source using gas sensors and anemometric sensors." Sensors and Actuators A: Physical 45(2): 153-157.

Ishida, H. and T. Nakamoto, et al. (1998). "Remote sensing of gas/odor source location and concentration distribution using mobile system." Sensors and Actuators B: Chemical 49(1-2): 52-57.

Khaleghi, B. and A. Khamis, et al. (2013). "Multisensor data fusion: A review of the state-of-the-art." Information Fusion 14: 28-44.

Kowadlo, G. and R. A. Russell (2006). "Using naïve physics for odor localization in a cluttered indoor environment." Autonomous Robots 20(3): 215-230.

Kowadlo, G. and R. A. Russell (2009). "Improving the robustness of naive physics airflow mapping, using Bayesian reasoning on a multiple hypothesis tree." Robotics and Autonomous Systems 57(6-7): 723-737.

Li, J. G. and Q. H. Meng, et al. (2011). "Odor source localization using a mobile robot in outdoor airflow environments with a particle filter algorithm." Autonomous Robots 30(3): 281-292.

Li, J. and J. Yang, et al. (2013). Estimating a Continuous Odor-patch Path using Discrete Measurements for Odor Source Localization. Proceedings of the 32nd Chinese Control Conference, Xi'an, China.

Li, W. and J. A. Farrell, et al. (2006). "Moth-inspired chemical plume tracing on an autonomous underwater vehicle." IEEE Transactions on Robotics 22(2): 292-307.

Lilienthal, A. J. and A. Loutfi, et al. (2006). "Airborne chemical sensing with mobile robots." Sensors 6(11): 1616-1678.

Lilienthal, A. and T. Duckett (2004). "Building gas concentration gridmaps with a mobile robot." Robotics and Autonomous Systems 48(1): 3-16.

Pang, S. and J. A. Farrell (2006). "Chemical plume source localization." IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics) 36(5): 1068-1080.

Russell, A. and D. Thiel, et al. (1994). Sensing odour trails for mobile robot navigation. Proceedings of IEEE International Conference on Robotics and Automation, San Diego, CA, USA, IEEE.

Sandini, G. and G. Lucarini, et al. (1993). Gradient driven self-organizing systems. Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems, Yokohama, Japan, IEEE.

Shafer, G. (1976). A Mathematical Theory of Evidence. Princeton, Princeton University Press.

Vergassola, M. and E. Villermaux, et al. (2007). "'Infotaxis' as a strategy for searching without gradients." Nature 445(7126): 406-409.

Zarzhitsky, D. and D. F. Spears, et al. (2005). Distributed robotics approach to chemical plume tracing. Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems, Edmonton, Alberta, Canada, IEEE.

Odour dispersion modelling in Austria

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Two classes of dispersion models are currently used for (regulatory) odour dispersion, namely Gauss and Lagrange models. These models generally predict time-averaged concentrations, often over one hour. Therefore, the models have to be adopted somehow to cope with short-term odour peaks which can be smelled by the human nose. Over the last years, the authors have developed an approach where the short-term peaks are parameterized according to atmospheric stability ("peak-to-mean" factors). This approach is used with the Austrian Odour Dispersion Model AODM, based on the Austrian regulatory Gauss model, and described here in detail. With the German Lagrange model LASAT as well as with the AUSTAL 2000 model, a factor 4 is used independent of the distance from the source and the meteorological conditions to account for short-term peak concentrations. The models predict the separation distance between odour sources and the adjacent residential area to protect it from excessive odour nuisance. Besides the description of the approach in AODM, the meteorological input data to run the model are of importance. An example of separation distances for a fictitious livestock unit is added.

1. Introduction

Environmental odour is a main nuisance besides noise and air pollution. Caused by urban sprawl, the annoyance potential due to industrial, agricultural and municipal odour sources is growing tremendously. Besides abatement technologies for the release of odourous substances, the application of separation distances between odour sources and residential area is an appropriate method to reduce nuisance. Separation distances can be obtained from dispersion models. Such models predict the ambient odour concentration on an hourly or half-hourly basis. This time series of concentration values allows a calculation of the percentage of the time in a year during which the threshold odour concentration will be exceeded. This can be compared to a tolerated exceedence probability depending on the land-use category. Combinations of threshold odour concentrations and tolerated exceedence probabilities are called odour impact criteria. An overview of various national odour impact criteria can be found in Sommer-Quabach et al. (2014).

Two pre-requisites are necessary to run this procedure: a transformation of the mean values calculated by the models to short-term concentrations relevant for human odour perception, and the appropriate meteorological input, i.e. representative wind and stability information for the site under investigation.

For Austria, to determine the short-term peak concentrations required for the assessment of odour perception, the authors developed a peak-to-mean approach depending on atmospheric stability; this algorithm is used in the Austrian Odour Dispersion Model (AODM), the regulatory Austrian Gauss model, and a description has been published already in Schauberger et al. (2000) and Piringer et al. (2007); in Piringer et al. (2014), the latest version is described in detail. With the German

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Lagrange model LASAT, a factor 4 is used independent of the distance from the source and the meteorological conditions to account for short-term peak concentrations (Janicke et al., 2004; Janicke Consulting, 2013). The discrepancy of the two concepts is discussed in Schauberger et al. (2012).
Dispersion models need mainly wind and stability information as meteorological input data. Whereas the use of wind data, either based on measurements or from meteorological pre-processors, is often straightforward, on-site representative stability information is more difficult to obtain. An overview on methods to determine discrete stability classes can be found e.g. in Piringer et al. (2004; Section 4.6) and Piringer & Schauberger (2013).
The structure of the paper is as follows: Section 2 presents a brief description of the models used, the peak-to-mean approach, and the model input data. The results and a discussion are presented in Section 3. Section 4 contains a summary and a brief outlook on current developments.

2. Material and methods

2.1 Brief description of the models used

The Austrian odour dispersion model (AODM; Piringer et al., 2007; Piringer et al., 2013; Schauberger et al., 2002) estimates mean ambient concentrations by the Austrian regulatory dispersion model and transforms these to instantaneous values depending on the stability of the atmosphere (Section 2.2). The model has been validated internationally with generally good results ((Baumann-Stanzer & Piringer, 2011; Piringer & Baumann-Stanzer, 2009). The regulatory model is a Gaussian plume model applied for single stack emissions and distances from 100 m up to 15 km. Plume rise formulae used in the model are a combination of formulae suggested by Carson & Moses (1969) and Briggs (1975). The model uses a traditional discrete stability classification scheme with dispersion parameters developed by Reuter (1970).
The dispersion model LASAT (Janicke Consulting, 2013) simulates the dispersion and the transport of a representative sample of tracer particles utilizing a random walk process (Lagrangian simulation). It computes the transport of passive trace substances in the lower atmosphere (up to heights of about 2000 m) on a local and regional scale (up to distances of about 150 km). A number of physical processes, including time dependencies, are simulated, such as transport by the mean wind field, dispersion in the atmosphere, sedimentation of heavy aerosols, deposition on the ground (dry deposition), washout of trace substances by rain and wet deposition, first order chemical reactions. The quality of the results achievable by Lagrangian models mainly depends on the wind field they are based on. A simplified version of LASAT is offered free of charge (AUSTAL2000, http://www.austal2000.de) which is favoured by German guide lines (GOAA, 2008; TA Luft, 2002). LASAT uses the Klug-Manier stability classification scheme (TA Luft, 2002). Like AODM, LASAT has been evaluated using test data sets for different applications (see www.janicke.de).

2.2 The Austrian peak-to-mean approach

The peak-to-mean concept in the AODM is based on a relationship by Smith (1973), where the peak-to-mean factor $\psi_0 = C_p / C_m$ is given by:

$$\frac{C_p}{C_m} = \left(\frac{t_m}{t_p}\right)^a \qquad (1)$$

with the mean concentration C_m calculated for an integration time of t_m (1800 s) and the peak concentration C_p for an integration time of t_p (5 s). The exponent a depends on atmospheric stability. The maximum peak-to-mean factor ψ_0 valid near the odour source varies between approx. 3 (stable conditions) and 55 (very unstable conditions). For the reduction of the peak-to-mean ratio with distance due to turbulent mixing, an exponential attenuation function (Mylne & Mason, 1991; Mylne, 1992) is used:

$$\Psi = 1 + (\Psi_0 - 1)\exp\left(-0.7317\frac{T}{t_L}\right) \quad (2)$$

where $T = x/u$ is the time of travel with the distance x and the mean wind speed u, t_L is a measure of the Lagrangian time scale (Mylne, 1992).

The time scale t_L is taken to be equal to σ^2/ε where $\sigma^2 = 1/3\left(\sigma_u^2 + \sigma_v^2 + \sigma_w^2\right)$ is the variance of the wind speed taken as the mean of the variance of the three wind components u, v, and w, respectively, and ε is the rate of dissipation of the turbulent energy using the following approximation:

$$\varepsilon = \frac{1}{k\,z}\left(\frac{\sigma_w}{1.3}\right)^3 \quad (3)$$

where $k = 0.4$ is the von Karman constant and $z = 2$ m is the height of the receptor, the human nose.

A relationship between the standard deviations of the three wind components and the mean wind speed u was proposed by Robins (1979) and is given in Tab. 1. For σ_u/u and σ_v/u, no change with stability is assumed. Deviating from Robins (1979), σ_w/u is taken in the AODM to be stability-dependant, assuming an increasing importance of σ_w compared to u in unstable conditions.

Table 1: Ratios of the standard deviations of the three wind components (σ_u, σ_v and σ_w) *to the horizontal wind velocity u depending on the stability of the atmosphere (Robins, 1979).*

Stability class		σ_u/u	σ_v/u	σ_w/u
2	very unstable	0.2	0.2	0.3
3	unstable	0.2	0.2	0.2
4	neutral	0.2	0.2	0.1
5	slightly stable	0.2	0.2	0.1
6	stable	0.2	0.2	0.1
7	very stable	0.2	0.2	0.1

The resulting peak-to-mean attenuation curves are presented in Fig. 1. For classes 2 and 3, the peak-to-mean factors, starting at rather high values near the source, rapidly approach 1 with increasing distance. This is in agreement with the premise that vertical turbulent mixing can lead to short periods of local high ground-level concentrations, whereas the ambient mean concentrations are low. For class 4, the decrease of the peak-to-mean ratio is more gradual with increasing distance, because vertical mixing is reduced and horizontal diffusion is dominating the dispersion process. The peak-to-mean ratio in 100 m is then about 4. The curve for class 5 is similar to that of class 4, with reduced absolute values. For classes 6 and 7 (identical curves due to identical ψ_0 values), the peak-to-mean ratio exceeds 2 only near the source. The grey horizontal line denotes the overall factor 4 of the German TA-Luft (2002). This factor clearly dominates from 100 m onwards. This has strong implications on the resulting separation distances, as will be shown in Section 3.

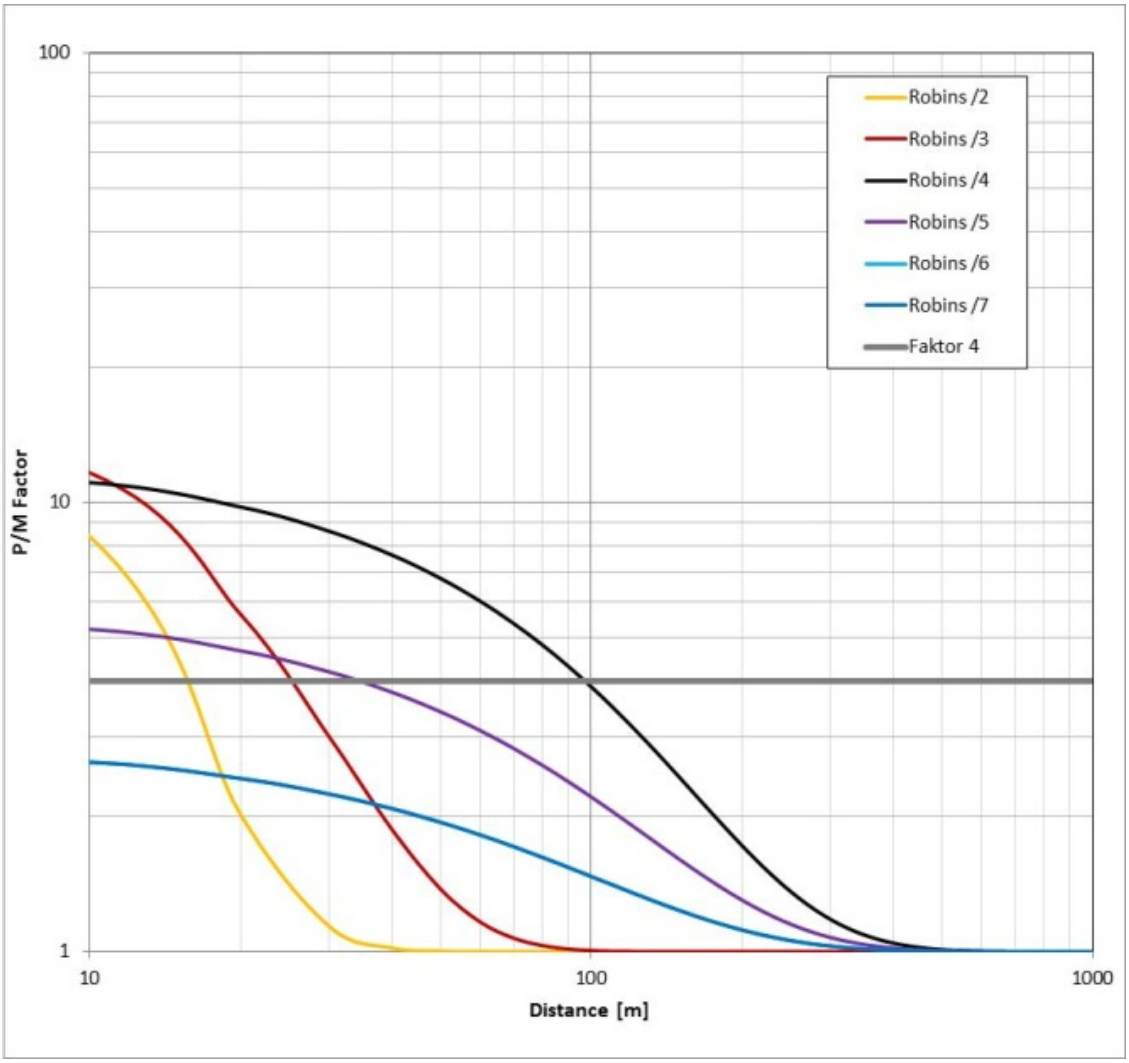

Figure 1: Peak-to-mean ratios depending on the distance from the source for different atmospheric stabilities (classes 2 to 7, definition see Tab. 1) and the overall factor 4 of the German TA-Luft.

2.3 Site and emissions

Separation distances have been calculated for the site Kittsee east of Vienna near Bratislava (17.070° E and 48.109 N at 136 m asl.). The site is within flat terrain, mainly farmland. Kittsee can experience high wind speeds, mainly from northwesterly directions, often associated with frontal systems and storms. The secondary maximum of wind directions is from northeast, in contrast to a lot of other meteorological stations in the area. This is explained by a topographical deflection of the regional flow in the area caused by the southernmost tip of the Carpathian mountains in the region of Bratislava north of the site. These wind directions show on average lower wind speeds as they are mainly observed in anti-cyclonic conditions.

For all model runs, the same source data are used (Tab. 2). The source is assumed non-buoyant, i.e. the effective stack height is equal to the physical stack height. As for the AODM and LASAT runs the same emissions, the same meteorological input data and the same peak-to-mean attenuation curves are used, the resulting separation

distances depend on the different model physics and differences in the schemes to determine atmospheric stability only.

Table 2: Source data for dispersion calculations

Stack height	[m]	8.0
Stack diameter	[m]	2.7
Outlet air velocity	[m s^{-1}]	3.0
Volume flow rate	[m^3 h^{-1}]	60 000
Temperature	[°C]	20
Odour emission rate	[$ou_E s^{-1}$]	5 200

3. Results and discussion

Direction-dependent separation distances are calculated for two odour impact criteria used in Austria: 1 ou_E/m3 and 3 % exceedence probability, representative for recreation areas (high odour protection), 1 ou_E/m3 and 8 % exceedence probability, representative for residential areas mixed with commercial activity (low odour protection). They are shown as isolines in Fig. 2, encompassing the area of exceedence of the given thresholds. The larger the area, the more unfavourable is the odour impact criterion. In Fig. 2, the AODM results are compared to the factor 4-model of TA-Luft (2002) applied with LASAT.

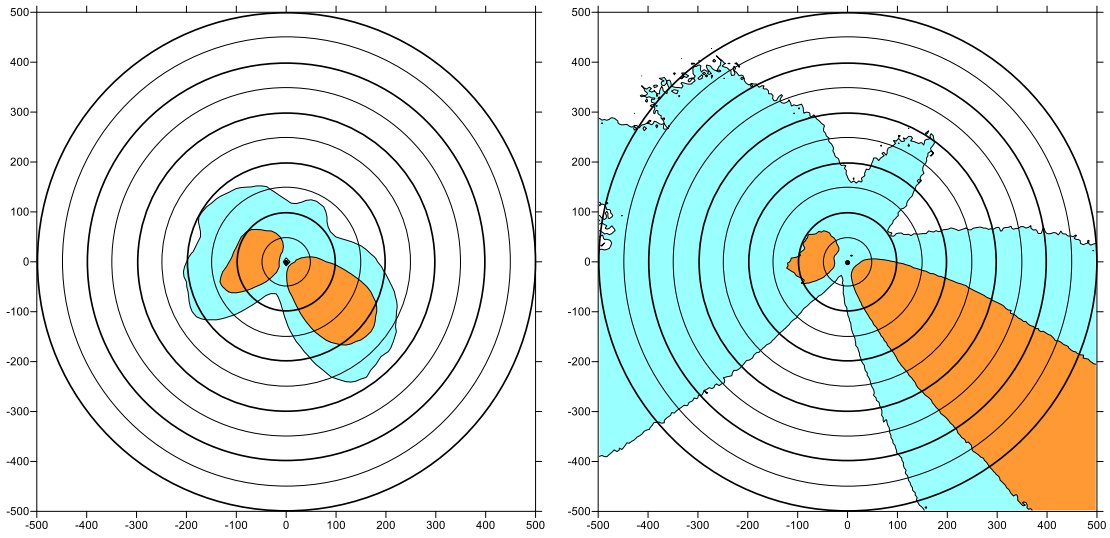

Figure 2: Direction-dependent separation distances [m] with (left) AODM, peak-to-mean ratios from Fig.1, and (right) LASAT, factor 4, for 1 ou_E/m3 and 3 % (blue) and 8 % (orange) exceedence probability for Kittsee.

Comparing the left and the right panel in Fig. 2, large differences in the separation distances can be seen. The application of an overall factor 4 over all distances and stability conditions clearly leads to very large, partly unrealistic separation distances. The shape of the separation distances is strongly influenced by the wind directions in Kittsee, and the elongation towards SE is due to the fact that north-westerly winds coincide with the highest wind speeds, on average. Allowing for an exceedence probability of 3 %, this elongation is much more pronounced for LASAT, where the separation distance towards SE well exceeds 500 m, compared to only 280 m for

AODM. Also towards the west, LASAT calculates far larger separation distances compared to AODM, for an exceedence probability of 3 %. For 8 %, however, the area of exceedence then is similar to AODM.
Apart from the use of the factor 4 with LASAT, another reason for the discrepancy of separation distances between AODM and LASAT originates from the different stability schemes used with the two models. Stability classes in Austria are determined with the Reuter (1970) scheme, those in Germany with the Klug-Manier scheme (TA-Luft, 2002). In both schemes, stability classes are determined as a function of half-hourly mean wind speed and a combination of sun elevation angle, cloud base height and cloud cover. In the Reuter (1970) scheme, classes 2 and 3 can occur only during daytime, classes 5 to 7 only at night. Class 4 can occur day and night. Klug-Manier classes are numbered from I to V and are classified according to atmospheric stability as follows: Stability classes V and IV comprise very unstable and unstable conditions. They do not occur during nighttime. Class V occurs only between May and September in Central Europe. Stability classes III/2 and III/1 are classified as neutral. III/2 occurs predominantly at daytime, III/1 predominantly at nighttime and during sunrise and sunset. Stability classes II and I comprise stable and very stable conditions, mostly, but not exclusively at night.

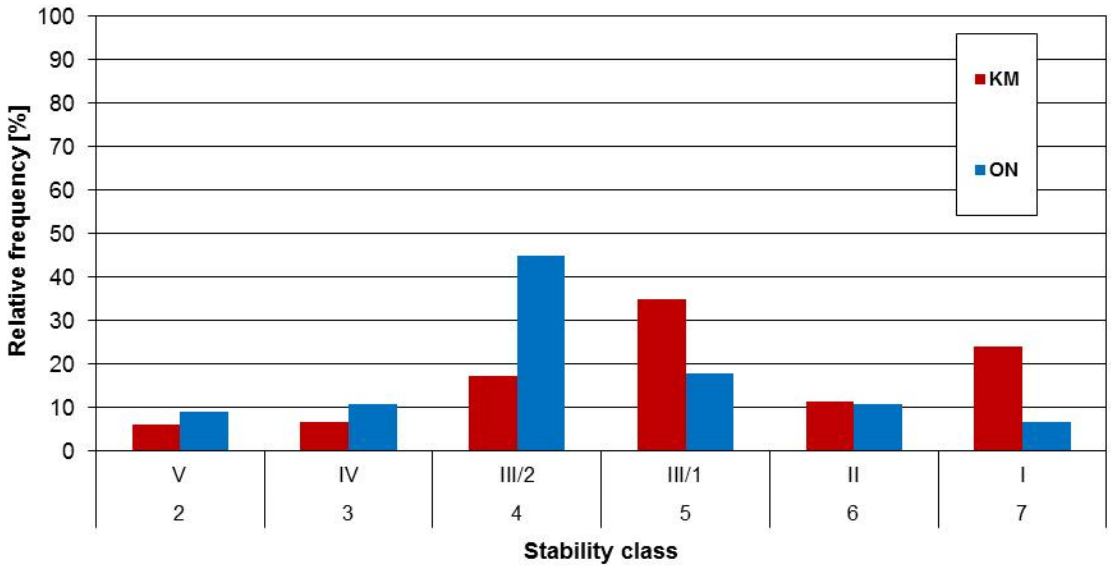

Figure 3: Relative frequency of stability classes in Kittsee; KM = Klug-Manier (TA-Luft, 2002); ON = Reuter (1970).

The Reuter (1970) scheme used in the AODM delivers about twice as many unstable situations for Kittsee compared to the Klug-Manier scheme (TA-Luft, 2002), whereas the latter calculates much more neutral and stable cases (Fig. 3). Thus, the large separation distances for NW wind calculated by LASAT are supported by the neutral and stable conditions which often occur with NW wind; only at shorter distances, the unstable classes 2 and 3 are relevant which are mainly observed with easterly winds. As unstable situations are very seldom in the Klug-Manier scheme, LASAT calculates similar separation distances compared to AODM for an exceeding probability of 8 % west of the odour source.

4. Conclusions and outlook

Separation distances to protect the neighbourhood from odour nuisance have been calculated with two models, the Gaussian Austrian Odour Dispersion Model AODM and the Lagrange particle diffusion model LASAT. Short-term peak odour concentrations have been calculated with the peak-to-mean ratios of Fig. 1 for AODM and with the factor 4 for LASAT. The same emission (Tab. 2) and meteorological data have been used, but atmospheric stability is determined differently from these data (Section 3). Differences in the resulting separation distances are then both due to the different peak-to-mean concepts and to the different atmospheric stability schemes used with the models. The results are demonstrated for Kittsee, a rural site in the Eastern flatlands of Austria near Bratislava.

The maximum of the separation distances occurs for NW wind and is thus stretching south-east; this can be explained by the fact that the main wind direction in Kittsee is also associated with the highest average wind speed and predominantly neutral to stable dispersion conditions. In this case, LASAT delivers unrealistically large separation distances, caused by the factor 4 and the stability scheme with LASAT which calculates far more neutral and stable situations occurring with NW wind than the AODM stability scheme. Allowing for an exceedence probability of 8 %, LASAT calculates similar separation distances as AODM for easterly winds, as these are mainly associated with unstable conditions, which are very seldom in the LASAT stability scheme compared to AODM.

Currently, a coupling of the peak-to-mean approach developed for AODM to LASAT is undertaken which is stimulated, apart from the large discrepancies in separation distances between LASAT and AODM with the current peak-to-mean ratios, also by the wider range of applicability of LASAT. It is commonly accepted that Gauss models can be used in flat terrain without nearby obstacles; Lagrange models have a broader range of applicability, including built-up areas and moderate topography.

References

Baumann-Stanzer, K. & Piringer, M. (2011). Validation of regulatory micro-scale air quality models: modelling odour dispersion and built-up areas. World Review of Science, Technology and Sust. Development, 8, 203-213.

Briggs, G. A. (1975). Plume rise predictions. Lectures on air pollution and evironmental impact analysis. AMS Report, Boston.

Carson, J. E. & Moses, H. (1969). Validity of several plume rise formulas. Air Pollution Control Assn-J, 19, 862-866.

GOAA (2008). Detection and Assessment of Odour in Ambient Air. Guideline on Odour in Ambient Air (GOAA).

Janicke Consulting (2013). Dispersion model LASAT. Reference/Working Book for Version 3.3.

Janicke, L., Janicke, U., Ahrens, D., Hartmann, U. & Müller, W.J. (2004). Development of the Odour Dispersion Model AUSTAL2000G in Germany. Environmental Odour Management, VDI-Berichte 1850, 411-417.

Mylne, K. R. (1992). Concentration fluctuation measurements in a plume dispersing in a stable surface layer. Boundary-Layer Meteorology, 60, 15-48.

Mylne, K. R. (1992). Concentration fluctuation measurements in a plume dispersing in a stable surface layer. Boundary-Layer Meteorology, 60, 15-48.

Mylne, K. R. & Mason, P.J. (1991). Concentration fluctuation measurements in a dispersing plume at a range of up to 1000m. Quarterly Journal of the Royal Meteorological Society, 117, 177-206.

Piringer, M. & Baumann-Stanzer, K. (2009). Selected results of a model validation exercise. Adv Sci Res, 3, 13-16.

Piringer, M. & Schauberger, G. (2013). Dispersion modeling for odour exposure assessment.. In V. Belgiorno, V. Naddeo & T. Zarra (Eds.), Odour Impact Assessment Handbook (Volume , pp. 125-176). Wiley.

Piringer, M., Joffre, S., Baklanov, A., Burzynski, J., Christen, A., Deserti, M., De Ridder, K., Emeis, S., Karppinen, A., Mestayer, P., Middleton, D., Tombrou, M., Baumann-Stanzer, K., Bonafè, G., Dandou, A., Dupont, S., Ellis, N., Grimmond, S., Guilloteau, E., Martilli, A., Masson, V., Oke, T., Prior, V., Rotach, M. & Vogt, R. (2004). The Urban Surface Energy Budget and Mixing Height in European Cities: Data, Models and Challenges for Urban Meteorology and Air Quality. Final Report of Working Group 2 of COST 715-Action.

Piringer, M., Knauder, W., Petz, E. & Schauberger, G. (2014). Use of Ultrasonic Anemometer Data to Derive Local Odourrelated Peak-to-mean Concentration Ratios. Chemical Engineering Transactions, 40, 103-108.

Piringer, M., Petz, E., Groehn, I. & Schauberger, G. (2007). A sensitivity study of separation distances calculated with the Austrian Odour Dispersion Model (AODM). Atmospheric Environment, 41, 1725-1735.

Piringer, M., Petz, E., Groehn, I. & Schauberger, G. (2013). Corrigendum to "A sensitivity study of separation distances calculated with the Austrian Odour Dispersion Model (AODM)" [Atmos. Environ. 41 (2007) 1725-1735]. Atmospheric Environment, 67, 461-462.

Reuter, H. (1970). Die Ausbreitungsbedingungen von Luftverunreinigungen in Abhängigkeit von meteorologischen Parametern. Arch. Met. Geoph. Biokl. A,, 19, 173-186.

Robins, A. G. (1979). Development and structure of neutrally simulated boundary layers. J. Industrial Aerodynamics, 4, 71 - 100.

Schauberger, G., Piringer, M. & Petz, E. (2000). Diurnal and annual variation of the sensation distance of odour emitted by livestock buildings calculated by the Austrian odour dispersion model (AODM). Atmospheric Environment, 34, 4839-4851.

Schauberger, G., Piringer, M. & Petz, E. (2002). Calculating Direction-dependent Separation Distance by a Dispersion Model to avoid Livestock Odour Annoyance. Biosyst Eng, 82, 25-37.

Schauberger, G., Piringer, M., Schmitzer, R., Kamp, M., Sowa, A., Koch, R., Eckhof, W., Grimm, E., Kypke, J. & Hartung, E. (2012). Concept to assess the human perception of odour by estimating short-time peak concentrations from one-hour mean values. Reply to a comment by Janicke et al.. Atmospheric Environment, 54, 624-628.

Smith, M. E. (1973). Recommended guide for the prediction of the dispersion of airborne effluents. ASME, New York.

TA Luft (2002). Erste Allgemeine Verwaltungsvorschrift zum Bundes–Immissionsschutzgesetz. (Technische Anleitung zur Reinhaltung der Luft - TA Luft).

Odour impact criteria to avoid annoyance

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To determine separation distances between odour sources and residential areas to avoid odour nuisance and complaints by the residents, odour impact criteria OIC have to be adopted by the responsible authorities. There is a wide variety of OIC used for this purpose, which differ by the odour concentration threshold (between 0.12 $ou_E\ m^{-3}$ and 10 $ou_E\ m^{-3}$), the averaging period (hourly or instantaneous) and by the tolerated exceedance probability of the adopted threshold (between 0.1% and about 35% of the time).
There are two groups of OIC used in various jurisdictions: the first one with a low odour concentration threshold and a high tolerated exceedance probability (e.g. Germany); and the second group with a high odour concentration threshold and a low tolerated exceedance probability (e.g. Ireland). The modelled direction-dependent separation distances (using OIC which are supposed to offer the same protection level) can vary significantly. The OIC of the second group, considering higher ambient odour concentrations, show a much lower sensitivity to site-specific meteorological data. Therefore, a higher tolerated exceedance probability seems more appropriate for the determination of OIC. Even if the similarity of separation distances by various OIC could be determined, the direction-dependent separation distances differ considerably for the same protection level for a certain receptor type, e.g. rural residential properties.

1. Direction dependent separation distance

The annoyance potential of odour sources can be assessed by separation distances. The direction dependent separation distance between odour sources and residential areas is used to divide the circumjacent area around a source in a zone which is protected from nuisance and a zone closer than the separation distance where nuisance can be expected and has to be accepted. The protection level depends also on the land use category; the higher the protection level, the farther the separation distance.
The direction-dependent separation distance between an odour source and the residential properties is the regulatory tool, which takes into account the entire chain starting from the odour emission rate (source strength), the dilution in the atmosphere (the dispersion model) and the evaluation of the predicted ambient concentration (the output of the dispersion model) against certain odour impact criteria OIC. In general, the OIC are set by the environmental agencies or other governmental institutions on a national basis.
The quantification of annoyance depends on various predictors which can be summarised by the FIDO factors (frequency, intensity, duration and offensiveness of the perceived odour) (Watts and Sweeten, 1995). In New Zealand (Ministry for the Environment New Zealand, 2003) and several countries in Europe, a fifth factor, the location, is additionally in use (FIDOL). This last factor describes the nuisance with regard to the sensitivity of the receiving environment which is taken into account by the zoning. The location factor can directly be compared to the factor reasonableness, suggested by Miner (1995). He defines reasonableness of odour sensation as odour

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causing fewer objections within a community where odour is traditionally part of the environment, e.g. for rural smells as part of the rural environment and for industrial smells in industrial areas. Problems also often arise when incompatible activities are located near each other. For example, complaints about existing intensive farming operations often occur when land use in the vicinity is changing. Personal knowledge of the operator of the livestock unit, long term residency, economic dependence on farming, familiarity with livestock farming and awareness of the agricultural-residential context are related to a reduced incidence of formal complaints. An assessment of this factor is often done by the land use (zoning) category of the neighbours, e.g. a pure residential area has a higher protection level as a rural site.
In most of the national jurisdictions which set up national odour impact criteria only the two dimensions “frequency” and “intensity” are used out of the FIDOL factors. The reasonableness and thereby the protection level for a certain zone, which is described by the dimension “location”, is considered by varying these two selected dimensions.

2. Odour impact criteria

For practical use separation distances are calculated to reduce or avoid odour annoyance depending on a certain protection level. At such a distance the frequency of odour sensation over a certain odour concentration threshold C_T does not exceed a pre-selected level, called the exceedance probability p_T. The exceedance probability can be defined as a conditional probability p_T = prob [$C|C > C_T$]. This concept is based on investigations of Miedema and Ham (1988) and Miedema et al. (2000) who found a strong relationship between the odour concentration threshold $C_{2\%}$ (respectively the 98 percentile) for an exceedance probability of p_T = 2% and the percentage of the highly annoyed neighbours HA, using an integration time of 1 hour (hourly mean values)

$$HA = K \log C_{2\%}$$

with a constant K = 9.25 (Miedema et al., 2000) or 10 < K <12 for pigs (Nicolas et al., 2008b).

2.1 National determination of OIC

Various national odour impact criteria NOIC which differ by the odour concentration threshold and exceedance probability are in use to protect inhabitants from the same level of nuisance.
Two examples of NOIC are given which differ considerably. In Germany the NOIC for pigs is defined by a low odour threshold of 0.25 ou m^{-3} (as an hourly mean value) and high exceedance probabilities of 20% for rural and 13.3% for urban areas. In Ireland an odour threshold of 6 ou m^{-3} for rural and 3 ou m^{-3} for urban areas with a low exceedance probability of 2% is in use.
This approach of OIC is used identically for all other odour sources (e.g. waste water treatment plants (Capelli et al., 2013), municipal solid waste landfills (Sironi et al., 2005).
The calculation of the separation distance is carried out using a dispersion model, which predicts the ambient odour concentration on an hourly basis. This time-series of concentration values allows a calculation of the percentage of time in the year during which the threshold odour concentration (OIC) would be exceeded. This can be compared to the tolerated exceedance probability.

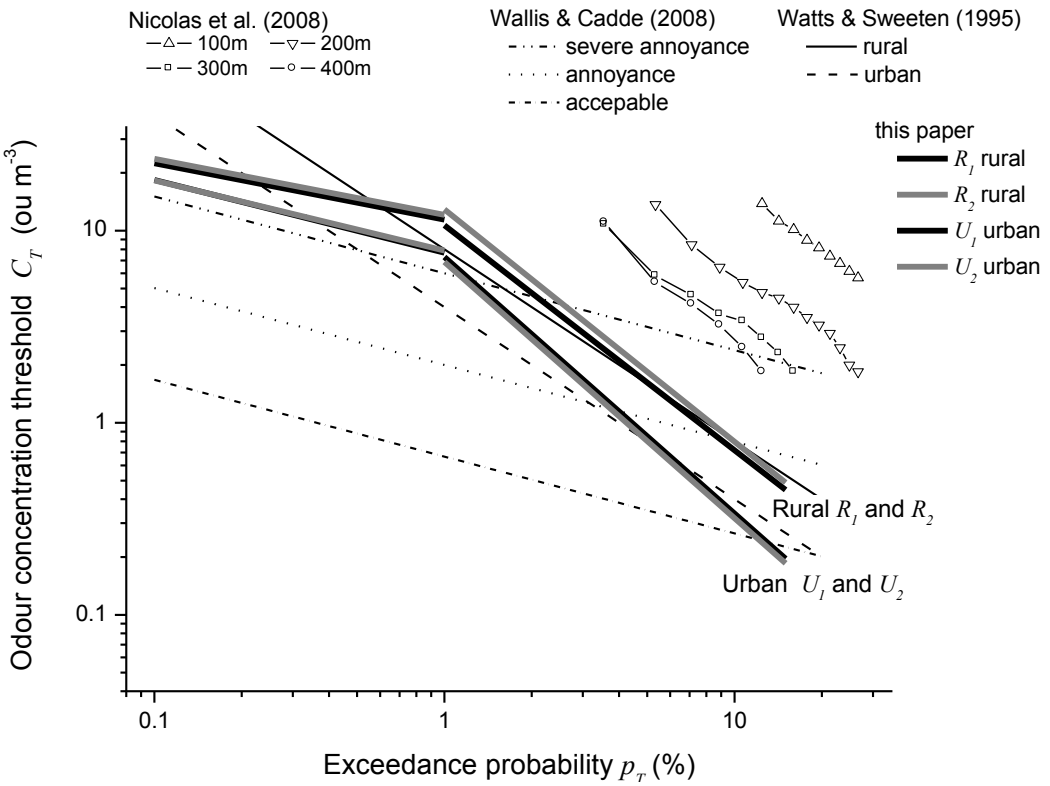

Figure 1: Relationship between exceedance probability p_T and odour concentration threshold C_T to define similar protection levels. The empirically derived functions are compared with the functions of Watts and Sweeten (1995) and Wallis and Cadee (2008). Additionally, empirical data are added for a pig farm (Nicolas et al., 2008a) (from Sommer-Quabach et al. (2014))

For a low exceedance probability of p_T = 2% or less only few distinct meteorological situations will contribute to the separation distance. For p_T = 0.1% (West Australia) only 9 hours are used to determine the separation distance. This means that for each wind direction at least nine hours per year of a certain meteorological situation with a very low dilution can be found which leads to a nearly circular separation distance. In contrast, for a high exceedance probability in the range of 10 to 20%, nearly all stability classes contribute to the separation distance as could be shown by Schauberger et al. (2006). Further on, the two isopleths of the protection levels of rural and urban residential areas show a higher discriminatory power for higher exceedance probabilities, because there the two isopleths have a greater distance (Figure 1). Even if the similarity of separation distances for various OIC can be determined, the direction dependant separation distances differ considerably for the same protection level.

2.2 Hedonic tone

The offensiveness of the odour perception, often measured in terms of “hedonic tone”, in the pleasantness–unpleasantness–dimension, is a powerful predictor of annoyance. It is shown that exposure-annoyance as well as exposure–symptom associations are strongly influenced by the hedonic tone. Whereas pleasant odours induced little to no annoyance, both neutral and unpleasant ones did (Sucker et al., 2008). In some countries (Germany, Ireland, and Belgium), the NOIC differ by the hedonic tone which means that for agricultural odour sources, the limit values depend on the kind of animals. This approach is suggested by the German odour guideline (GOAA, 2008) not

only for odour emission caused by animal husbandry but also for all other odour sources. There a methodology is included into the guideline to judge if a perceived odour is closer to a pleasant smell or unpleasant malodour. According to the proximity to one of these two poles, the exceedance probability of the OIC can be adapted by using a weighting factor f. Then the nuisance relevant exceedance probability p_T* is calculated by $p_T* = p_T / f$. For an unpleasant odour (e.g. broilers with f = 1.5) the tolerated exceedance probability for pure residenatal areas is then reduced from 10% to $p_T* = 6.7\%$, for a more pleasant odour (e.g. dairy cattle with f = 0.5) the tolerated exceedance probability is increase to 20%.

2.3 Resonableness and protection level

Besides the hedonic tone also the reasonableness of odour sensation has a strong influence on the annoying potential. Taking the 10% value of annoyed people, the corresponding concentration threshold C_T for the exceedance probability of p_T = 2% (1-hour mean value) is C_T = 1.3 ou m^{-3} for the general public. In areas dominated by agricultural land use, the “acceptable” concentration reaches C_T = 3.2 ou m^{-3}. If pig odour is a historical feature of the environment, then C_T = 6.3 ou m^{-3}. For those inhabitants which are directly involved in livestock husbandry, the concentration is determined to C_T = 13 ou m^{-3} (EPA Ireland, 2001). These findings are good arguments that OIC can be adapted according to zoning and to the acceptance of a certain odour level by residents. For the German NOIC the protection level is adapted to a certain zoning by the variation of the exceedance probability (e.g. for residential areas p_T = 10%, for rural areas p_T = 15%), whereas in most of the other countries, this is done by the variation of the odour threshold concentration C_T.

3. Calculation of the separation distance

3.1 Empirical guidelines

Some countries have already developed guidelines to address odour from livestock. In all these guidelines, the separation distance is calculated as a function of the odour emission rate, sometimes parameterized by the number of animals. Recently new guidelines were published for Germany (Schauberger et al., 2012d; VDI 3894 Part 2E, 2011), for Belgium (Nicolas et al., 2008a), and for the US (Nimmermark et al., 2005). In Austria a new guideline is under development which will substitute the old version published in 1995 (Schauberger and Piringer, 1997), which will include the empirical approach by Schauberger et al. (2012a).

The structure of these guidelines is mostly very similar. On the basis of the odour emission rate E (in ou$_E$/s), the separation distance S is calculated by an empirical function. In many cases the selected relation is a power function $S = a\,E^b$ (Schauberger et al., 2012d) with a factor a and the exponent b which are derived empirically. The predictors for these two parameters are the meteorological situation (e.g. frequency of the wind direction and wind velocity) and the selected protection level for the separation distance.

3.2 Dispersion models

Two classes of dispersion models are currently used for topics of (regulatory) odour dispersion, namely Gauss and Lagrange models. Both model classes belong to the so-called non-CFD (computational fluid dynamics) models. Generally, different grades of approximations and simplifications to the primitive equations are used when calculating concentrations. For example, these models do not calculate the flow around a single

building or obstacle when applied to an urban-like geometry, but the effect of a group of obstacles is taken into account through an increased surface roughness value or by a coarse resolution of the buildings. Non-CFD dispersion models are in general less complex and easier to run than typical CFD models and require much shorter calculation time. One main advantage is that non-CFD models may be run over a long series of input data to represent different meteorological conditions.
In Gauss models, flow-disturbing features like building influence or topography can only be treated via simple empirical relations and assumptions (e.g. flow around or across an isolated hill via the dividing streamline concept). In Lagrange models including a diagnostic wind field model, a more realistic simulation of the flow field due to topography or buildings is possible. A simple assessment of the ambient odour concentration in the near field of buildings can be found in Schauberger and Piringer (2004). For all types of models a meteorological station representative for the area of interest has to be chosen or erected to deliver the desired time series of meteorological parameters, at least over one whole year, in the form of hourly or half-hourly mean values. Additionally the atmospheric stability has to be derived from meteorological data or observations (e.g. cloud cover of a nearby airport) on an hourly basis.
The output of these dispersion models is the ambient concentration at a certain point with the same temporal resolution in the form of hourly or half-hourly mean values.

3.3 Assessment of the perceived odour concentration in the field

Contrary to most air borne pollutants odour is not a feature of a certain chemical species but a physiological reaction of humans. The sensation and perception of odorants depends on sniffing as an active stage of stimulus transport.
For the assessment of peak values, describing the biologically relevant exposure, often the so called peak-to-mean concept is used. This is a way to adopt dispersion models to short-term odour concentrations. The goal of the use of peak-to-mean factors is to mimic the perception of the human nose in a better way as it can be achieved by long term mean values.
The step from the one-hour mean value (as output of the dispersion model) to an instantaneous odour concentration is shown in Figure 2. For the one-hour mean value, the threshold for odour perception (here taken as 1 ou_E/m^3) is not exceeded. Taking mean values over 10 minutes, one concentration value exceeds the threshold. For the short term mean values of 12 s, concentrations in the range of 5 to 6 ou_E/m^3 can be expected, which means a distinct odour perception over several breaths. Figure 2 shows that the shorter the selected time interval, the higher the maximum concentration. For the shortest period of 12 s, a new feature of the time series can be seen. Besides 12 s intervals with odour concentrations above zero, a certain percentage of zero observations can be expected. The frequency of non-zero intervals is called intermittency (Chatwin and Sullivan, 1989).
Therefore, the maximum ambient odour concentration for a single breath C_p can be estimated using a peak-to-mean factor F which modifies the modelled odour concentration (one hour mean C_m) using $C_p = C_m F$. The shorter the integration time for the ambient odour concentration, the higher the peak-to-mean factor F. It is assumed that this peak concentration C_p is more appropriate to describe the odour sensation of the human nose than the one-hour mean value (Piringer and Schauberger, 2013; Schauberger et al., 2012b).
The following predictors are discussed, which influence the concentration fluctuation and thereby the peak-to-mean factor (Hanna and Insley, 1989; Olesen et al., 2005):

1. Stability of the atmosphere
2. Intermittency
3. Travel time or distance from the source
4. Lateral distance from the axis of the wake
5. Geometry of the source (emission height and source configuration)

The details for the parameterization of these five predictors can be found in Schauberger et al. (2012c).

A post-processing tool for dispersion calculations was developed by Schauberger et al. (2000) showing a decrease of the peak-to-mean factor with distance from the source. Further downwind the peak-to-mean factor is modified by an exponential attenuation function depending on the Lagrangian time scale (Piringer et al., 2007).

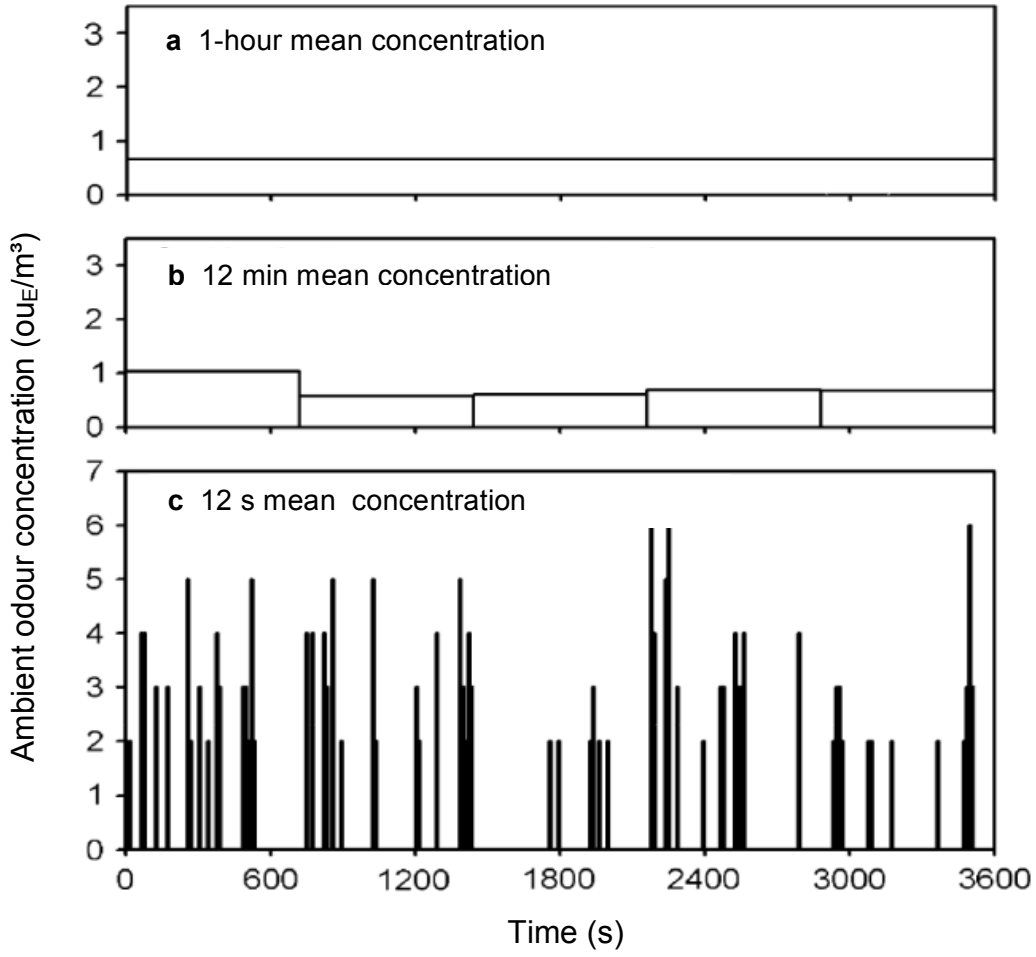

Figure 2: Time course of the odour concentration (ou_E /m³) for three time intervals. (a) one-hour mean value (e.g. output of a dispersion model), (b) 12-min and (c) 12-s mean odour concentrations observed at a single receptor point during a field study. The 12-s mean values were recorded and subsequently used to calculate 12-min and one-hour mean concentrations (source: Schauberger et al. (2012c), modified from Nicell (2009)).

To apply the NOIC properly, the relevant integration interval for the odour concentration has to be known.

4. Conclusions

In many countries, odour impact criteria OIC are in use defined as the combination of odour concentration threshold (in ou m^{-3}) and exceedance probability (in %). A commitment of the environmental authorities for OIC, which guarantees a certain protection level depending on the zoning, is an important feature for a reliable planning process.

References

Capelli, L., Sironi, S., Del Rosso, R., Guillot, J.-M., 2013. Measuring odours in the environment vs. dispersion modelling: a review. Atmos. Environ. 79, 731-743.

Chatwin, P.C., Sullivan, P.J., 1989. The intermittency factor of scalars in turbulence. Phys. Fluids A 1, 761-763.

EPA Ireland, 2001. Odour Impacts and Odour Emission Control Measures for Intensive Agriculture, Environmental Research, R&D Report Series No. 14. Environmental Protection Agency, Ireland.

GOAA, 2008. Guideline on Odour in Ambient Air (GOAA). Detection and Assessment of Odour in Ambient Air.

Hanna, S.R., Insley, E.M., 1989. Time series analyses of concentration and wind fluctuations. Bound-Lay. Meteorol. 47, 131-147.

Miedema, H.M.E., Ham, J.M., 1988. Odour annoyance in residential areas. Atmos. Environ. 22, 2501-2507.

Miedema, H.M.E., Walpot, J.I., Vos, H., Steunenberg, C.F., 2000. Exposure-annoyance relationships for odour from industrial sources. Atmos. Environ. 34, 2927-2936.

Miner, J.R., 1995. A review of the literature on the nature and control of odors from pork production facilities. National Pork Producers Council.

Ministry for the Environment New Zealand, 2003. Good Practice Guide for Assessing and Managing Odour in New Zealand. Ministry for the Environment, Wellington, New Zealand.

Nicell, J.A., 2009. Assessment and regulation of odour impacts. Atmos. Environ. 43, 196-206.

Nicolas, J., Delva, J., Cobut, P., Romain, A.-C., 2008a. Development and validating procedure of a formula to calculate a minimum separation distance from piggeries and poultry facilities to sensitive receptors. Atmos. Environ. 42, 7087-7095.

Nicolas, J., Romain, A., Delva, J., Collart, C., Lebrun, V., 2008b. Odour annoyance assessment around landfill sites: methods and results, NOSE 2008. International Conference on Environmental Odour Monitoring and Control Rome, Italy, pp. 29-36.

Nimmermark, S.A., Jacobson, L.D., Schmidt, D.R., Gay, S.W., 2005. Predictions by the Odor from Feedlots, Setback Estimation Tool (OFFSET) compared with observations by neighborhood monitors. J. Air Waste Manag. Assoc. 55, 1306-1314.

Olesen, H., Løfstrøm, P., Berkowicz, R., Ketzel, M., 2005. Regulatory odour model development: Survey of modelling tools and datasets with focus on building effects, NERI Technical Report No 541. National Environmental Research Institute, Ministry of the Environment, Denmark, p. 62.

Piringer, M., Petz, E., Groehn, I., Schauberger, G., 2007. A sensitivity study of separation distances calculated with the Austrian Odour Dispersion Model (AODM). Atmos. Environ. 41, 1725-1735.

Piringer, M., Schauberger, G., 2013. Dispersion modelling for odour exposure assessment, in: Belgiorno, V., Naddeo, V., Zarra, T. (Eds.), Odour Impact Assessment Handbook. Wiley, pp. 125-176.

Schauberger, G., Piringer, M., 1997. Guideline to assess the protection distance to avoid annoyance by odour sensation caused by livestock husbandry, in: Bottcher, R.W., Hoff, S.J. (Eds.), 5th International Livestock Environment Symposium ILES V. ASAE, St. Joseph, MI.

Schauberger, G., Piringer, M., 2004. Assessment of the odour concentration in the near-field of small sources, in: VDI (Ed.), European Conference on Environmental Odour Management. VDI Berichte 1850, Cologne, Germany, pp. 343-352.

Schauberger, G., Piringer, M., Jovanovic, O., Petz, E., 2012a. A new empirical model to calculate separation distances between livestock buildings and residential areas applied to the Austrian guideline to avoid odour nuisance. Atmospheric Environment 47, 341-347.

Schauberger, G., Piringer, M., Petz, E., 2000. Diurnal and annual variation of the sensation distance of odour emitted by livestock buildings calculated by the Austrian odour dispersion model (AODM). Atmos. Environ. 34, 4839-4851.

Schauberger, G., Piringer, M., Petz, E., 2006. Odour episodes in the vicinity of livestock buildings: A qualitative comparison of odour complaint statistics with model calculations. Agriculture, Ecosystems and Environment 114, 185-194.

Schauberger, G., Piringer, M., Schmitzer, R., Kamp, M., Sowa, A., Koch, R., Eckhof, W., Grimm, E., Kypke, J., Hartung, E., 2012b. Concept to assess the human perception of odour by estimating short-time peak concentrations from one-hour mean values. Atmospheric Environment 54, 624-628.

Schauberger, G., Piringer, M., Schmitzer, R., Kamp, M., Sowa, A., Koch, R., Eckhof, W., Grimm, E., Kypke, J., Hartung, E., 2012c. Concept to assess the human perception of odour by estimating short-time peak concentrations from one-hour mean values. . Atmospheric Environment 54, 624-628.

Schauberger, G., Schmitzer, R., Kamp, M., Sowa, A., Koch, R., Eckhof, W., Eichler, F., Grimm, E., Kypke, J., Müller, W.J., Hartung, E., 2012d. Empirical model derived from dispersion calculations to determine separation distances between livestock buildings and residential areas to avoid odour nuisance. Atmos. Environ. 46, 508-515.

Sironi, S., Capelli, L., Centola, P., Del Rosso, R., Grande, M.I., 2005. Odour emission factors for assessment and prediction of Italian MSW landfills odour impact. Atmos. Environ. 39, 5387-5394.

Sommer-Quabach, E., Piringer, M., Petz, E., Schauberger, G., 2014. Comparability of separation distances between odour sources and residential areas determined by various national odour impact criteria. Atmospheric Environment 95, 20-28.

Sucker, K., Both, R., Bischoff, M., Guski, R., Krämer, U., Winneke, G., 2008. Odor frequency and odor annoyance Part II: Dose - Response associations and their modification by hedonic tone. Int. Arch. Occup. Environ. Health 81, 683-694.

VDI 3894 Part 2E, 2011. Emissions and their impact from livestock operations. Method to determine the separation distance for odour. Beuth, Berlin.

Wallis, I., Cadee, K., 2008. Odour exposure criteria and odour modelling in Western Australia. Water 35, 144-148.

Watts, P., Sweeten, J., 1995. Toward a better regulatory model for odour, Feedlot Waste Management Conference 12-14 June 1995, Toowoomba, Queensland.

Experimental comparison of random search strategies for multi-robot based odour finding without wind information

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Abstract

In this paper, three random search strategies are implemented and compared in odour finding using multiple robots. The first strategy is Brownian walk (BW). As a typical uncorrelated random search strategy, BW combines a Gaussian distribution of move length with a uniform distribution of turning angles. Another two strategies are correlated random search strategies, namely correlated random walk (CRW) and Levy walk (LW). CRW and LW are obtained by replacing the distribution of move lengths and turning angles in BW with wrapped Cauchy distribution and Levy distribution, respectively. Experiments with the three random search strategies were conducted using four MrCollie robots in our laboratory. Results show that the two correlated random search strategies (i.e., CRW and LW) are more time-efficient than BW, and that LW obtains higher time-efficiency than CRW with respect to our experimental setup.

1. Introduction

Recent advances in microelectronics have accelerated the investigation on artificial olfactory systems, which can be divided into passive olfaction and active olfaction (Meng and Li, 2006). The former concerns mainly about the discrimination of different odours by processing olfaction-related signals (Jing et al., 2014), while the latter investigates the problem of controlling mobile olfactory mechatronic devices to locate the source of odour plume. In active olfaction, which is considered in this paper, autonomous mobile robots equipped with olfactory sensors are commonly utilized. Potential applications of active olfaction cover locating toxic or harmful gas/odour leakage source, humanitarian demining, and fighting against terrorist attacks, etc. Compared with skilled professionals and trained animals, robots are immune from chemical injuries, and thus, are more robust and more flexible.

The process of robot-based odour source localization comprises three alternating sub-processes (Lilienthal et al., 2006): odour finding (OF), odour source tracing, and odour source declaration. OF is conducted at the initial stage of odour source localization and ended when the robot detects the odour for the first time. After the first odour detection event, the robot searches for the odour source based on collected odour information. Then, if a certain condition is satisfied, the robot starts to declare whether the odour source lies at a nearby region or not. Obviously, OF serves as the basis of the other two sub-processes. Compared with the vigorous studies on odour source tracing and declaration, investigations concerning OF are really rare. Moreover, part of these investigations focused on the case of utilizing only a single robot, which means even fewer published works have concerned about OF based on multiple robots.

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To the author's knowledge, two representative systematic search strategies (Bartumeus et al., 2005) were proposed for multi-robot based OF. Li et al (Li, 2009) proposed a scattering strategy which makes the robots scatter with equal angel spans from the start and bounce back when any robot hits the edge of valid search region (VSR). Marjovi et al (Marjovi and Marques, 2013) proposed to move a line formation of robots along the upwind direction, which forms a sweeping search strategy. Both the scattering and sweeping strategies utilize deterministic algorithms, and thus are systematic strategies. Another important class of search strategies are random search strategies (Bartumeus et al., 2005), which rely on stochastic processes. Pasternak et al (Pasternak et al., 2009) simulated four random search strategies: Brownian walk (BW), correlated random walk (CRW), Levy walk (LW), and Levy taxis, in the context of finding the filamentous odour plume using a single robot in a ventilated environment. However, Pasternak's work lacks of real experimental results and results with respect to multiple robots. In environments with weak airflow, the less-dispersed odour distribution increases the difficulty of OF. The performance of these random search strategies on multi-robot based OF in real weak airflow environments needs further evaluation and comparison.

In this paper, we implement the BW, CRW, and LW strategies on multi-robot based OF in a closed indoor environment, where the wind information cannot be acquired using normal anemometers. Levy taxis is not considered since it needs real-time wind information. It is common to define random search strategies by the probabilistic distribution of the move lengths (MLs) and turning angles (TAs) at different steps. In each step, a new position is calculated based on ML, TA, and the old position. Being an uncorrelated random search strategy, which do not account for directional persistence (DP) (Bartumeus et al., 2005), BW utilizes a Gaussian distribution of MLs and a uniform distribution of TAs. Based on BW, DP is incorporated in CRW and LW by replacing the distribution of TAs and MLs with wrapped Cauchy distribution (WCD) and Levy distribution, respectively. Real multi-robot odour finding experiments were conducted to test whether DP increases the search efficiency or not and which of the BW, CRW, and LW strategies is the most time-efficient.

The rest of this paper is organized as follows: the real robots and odour source used in the experiments, as well as the test scenario, are introduced in section 2; the implementation of BW, CRW, and LW are described in section 3; experimental results are proposed and discussed in section 4; conclusions are given in section 5.

2. Materials and methods

2.1 MrCollie robots

Four isomorphic MrCollie (i.e., Mobile Robots for Cooperative Odour-source LocaLization in Indoor Environments) robots (Cao et al., 2015) were used in our experiments. One of the MrCollie robots is shown in Fig. 1. A metal-oxide-semiconductor sensor (MICS-5521, SGX sensor technology) is sustained by a pillar on the front side of the robot. Eight ultrasonic sensors and eight infrared sensors are mounted around the robot to detect the remote (0.8 m~3 m) and nearby (0 m~0.8 m) obstacles, respectively. An anemometer (WindSonic, Gill instruments) is mounted on the top of the robot. Although the anemometers were not used in our experiments, they were not removed so as to keep the integrity of the robots. On top of the anemometer, there is an identification label, which records orientation, index, and global position of

the robot. Through ultra-high-frequency radio waves, the robots periodically sent their concentration measurements to and received movement commands from a workstation. By processing the image acquired by a hard-wired CCD camera (DFx 31BG03, Imaging source technology) mounted on the ceiling, the workstation can recognize the information recorded by the identification labels, thereby the pose of each robot could be obtained.

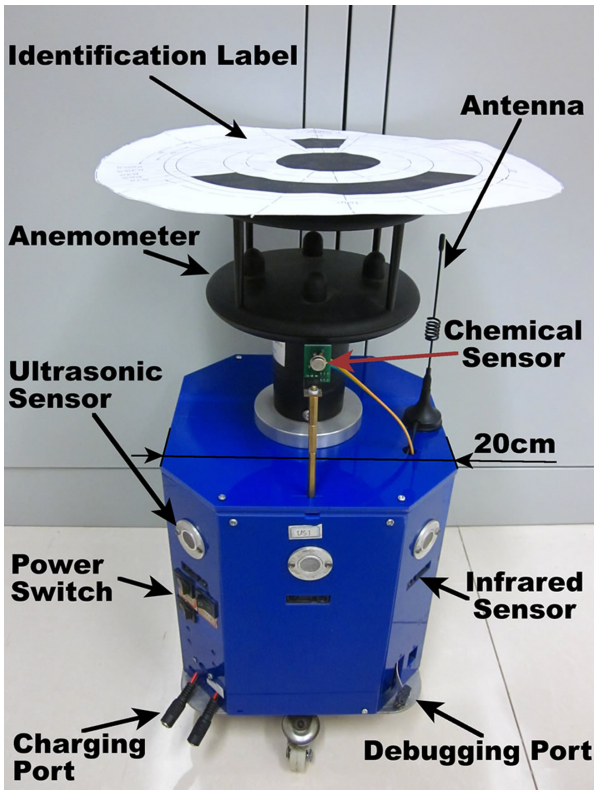

Figure 1: One of the MrCollie robots.

To determine odour detection events, only binary odour measurements are needed. As a typical MOS senor, the MICS-5521 sensor suffers from the problem of slow recovery time. To solve this problem, the odour detection event was determined by comparing the raw concentration measurement of MICS-5521, i.e., c_k, with an adaptive threshold, i.e., $\overline{c_k}$, which is defined as (Li et al., 2011):

$$\overline{c}_k = \begin{cases} \lambda \overline{c}_{k-1} + (1-\lambda) c_k, & k \geq 0 \\ c_k, & k = 0 \end{cases} \quad (1)$$

where λ is a predefined constant parameter. The value of λ was set to 0.5 in (Li et al., 2011). It was verified in (Cao et al., 2015) and (Neumann et al., 2013) that setting λ to 0.5 can effectively reflect realistic chemical contact. Based on equation (1), the case of $c_k > \overline{c_{k-1}}$ indicates an odour detection event at the k-th time step. Otherwise, a non-detection event is considered.

2.2 Odour source

As shown in Fig. 2, a self-made odour source that can generate atomized ethyl alcohol was used in our experiments. The main body of the odour source is a plastic bucket.

Absolute ethyl alcohol is placed inside of the bucket and atomized by the eight ultrasonic transducers. Eight ultrasonic transducers are placed at the bottom of the bucket to atomize the ethyl alcohol. Then, atomized ethyl alcohol odour is drown out from the bucket by the electronic fan. The odour source (i.e., the fan and ultrasonic transducers) was powered on for only about ten seconds before each experiment. If the odour source was powered on through the whole process of experiments, ethanol odour would be dispersed all over the lab. In that case, it is quite easy for the robots to encounter the ethanol odour, while it is not conducive to test the efficiency of OF methods.

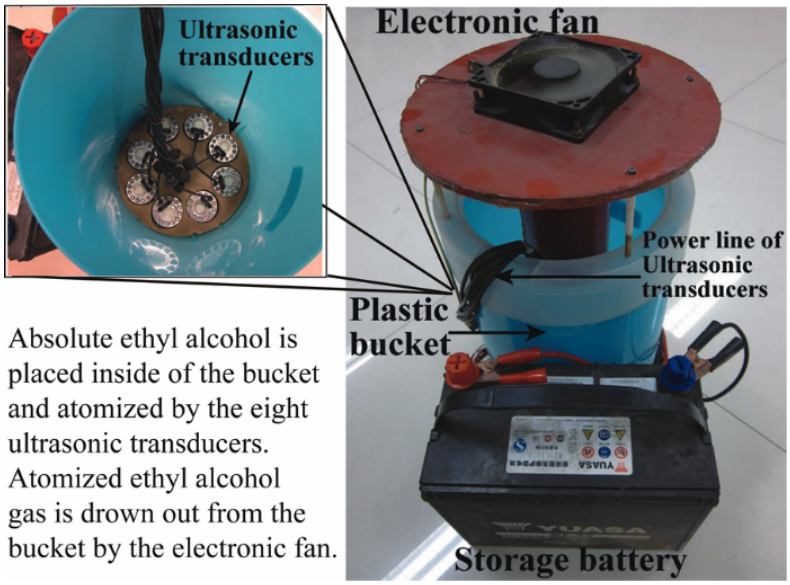

Figure 2: The schematic of the electronic nose

2.3 Test-bed scenario

All experiments were conducted in our lab, which is shaped like an irregular polygon as shown in Fig. 3. The VSR is a 5 m-by-7 m rectangular area. The odour source was placed at the north-east corner of the VSR. To maximize the difficulty of finding the odour plume, the robots started from the diagonal corner of the VSR. Correspondingly, the initial heading of the robots were equally distributed in the right angle covering the VSR.

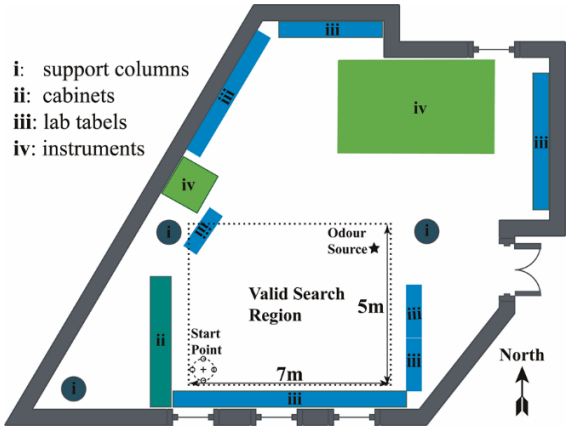

Figure 3: The experimental scenario.

3. Methods

Three search strategies were tested in this paper. To implement these search strategies for robot-based OF, the robot control architecture shown in Fig. 4 was utilized. As shown in Fig. 4, the search strategies output goal positions for the robots. If the robots move towards their goal positions along straight routes, they would collide with each other. Thus, the artificial potential field (APF) based motion planning method, which generates mutual repulsive force between nearby robots, is used for obstacle avoidance among the robots. Moreover, as long as the robot does not arrive at its goal position, the APF-based motion planning continuously generates attractive force for the robot from its goal position. Once the robot arrives at its goal position, a new goal position is generated according to the search strategies.

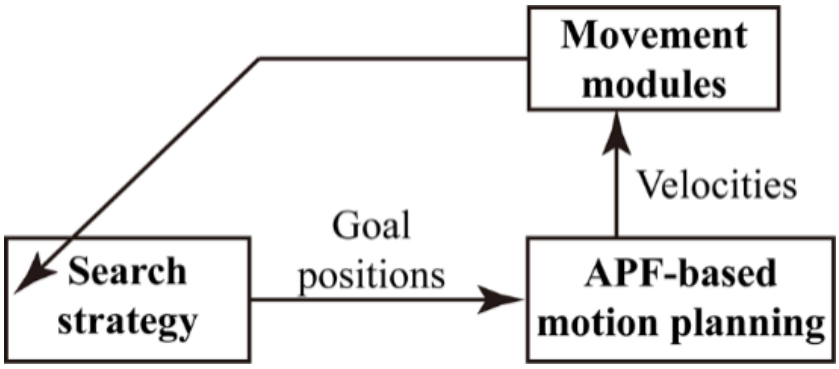

Figure 4: Control architecture for robot-based OF.

In the context of robot-based OF using random search strategies, new goal position of the robots are calculated as follows:

$$\begin{cases} x_{new} = x_{old} + l \cdot \cos(\theta + \Delta\theta) \\ y_{new} = y_{old} + l \cdot \sin(\theta + \Delta\theta) \end{cases} \quad (2)$$

where x_{new} (y_{new}) and x_{old} (y_{old}) are the coordinates of the new and old goal positions, respectively; θ is the current heading angle of the robot; l and $\Delta\theta$ are the ML and TA, respectively.

3.1 Brownian walk

As a typical uncorrelated random search strategy, BW does not account for DP in the movement. Thus, BW was used as a benchmark strategy to reveal the impact of DP on the OF efficiency without wind information. BW involves a Gaussian distribution for the MLs and a uniform distribution for the TAs. In our experiments, the MLs and TAs of BW were sampled from $N(1\ m,1)$ and $U(0,2\pi)$, respectively.

3.2 Correlated random walk

CRW utilizes a WCD of TAs, which is a non-uniform distribution, combining with a Gaussian distribution of MLs. In other words, DP is realized by controlling the probability distribution of TAs. The probability density function of the WCD is as follows (Pasternak et al., 2009):

$$p(\Delta\theta) = \frac{1-\rho^2}{2\pi\left(1+\rho^2-2\rho\cos\left(\Delta\theta\right)\right)}, \rho \in [0,1] \quad (3)$$

where ρ, $0 \leq \rho \leq 1$ is the shape parameter. Based on equation (3), the TAs in CRW are calculated as follows (Pasternak et al., 2009):

$$\Delta\theta = 2\arctan\left(\frac{\left(1-\rho\right)\cdot\tan\left(\pi\cdot\left(r-0.5\right)\right)}{1+\rho}\right) \quad (4)$$

where r is a uniformly distributed random variable within the range of [0,1]. According to equation (4), the TAs in CRW are distributed around zero. Thus, new position is most likely generated at the same direction as in the previous step, which brings about DP. In our experiments, ρ was set to a medium value in its range: ρ = 0.5.

3.3 Levy walk

LW utilizes Levy distribution as the distribution of the MLs while still retaining the uniform distribution of the TAs as in BW. The probability of generating long MLs in LW is higher than that in BW. Obviously, long ML brings about DP with respect to the current moving direction, which is different from the DP realized by controlling the probabilistic distribution of TAs in the CRW. The ML in LW is calculated as follows (Pasternak et al., 2009):

$$l = l_0 \cdot r^{\frac{1}{1-\mu}} \quad (5)$$

where l_0 is the minimal value of MLs, $\mu(1 \leq \mu \leq 3)$ is the Levy index, and $r(r \in [0,1]$ is a uniformly distributed random variable. According to equation (5), smaller value of μ yields lower probability of long MLs and degree of DP. Conversely, the bigger the value of μ, the higher the probability of long MLs and the degree of DP. In our experiments, l_0 and μ were set to 1 m and 2, respectively.

4. Results and Discussion

Each of the BW, CRW, and LW strategies was tested for several times. Then, two criteria were used to summarize the experimental results. The first is success rate. If the robots detected the odour in four minutes after the start, the correlated trial is considered successful. The success rate was calculated as the ratio of successful trials in the corresponding group of experiments for each random search strategy. The second is the average time spent in each group of successful trials, which means the time spent in failed trials were not summarized in the average time.

Table 1: Ratios of the standard deviations of the three wind components (σ_u, σ_v and σ_w) *to the horizontal wind velocity u depending on the stability of the atmosphere (Robins, 1979).*

	BW	CRW	LW
Success rate	2/13	12/14	**13/14**
Average time (s)	227	156	**104**

The success rates and average time spent in successful trials are shown in Tab. 1. BW succeeded in only 2 out of 13 trials, and the average time spent by BW is close to the

time limit, i.e., 240 seconds (four minutes). CRW and LW succeeded in most of the corresponding trials and yielded much higher success rates than BW. Moreover, LW spent less average time than CRW.

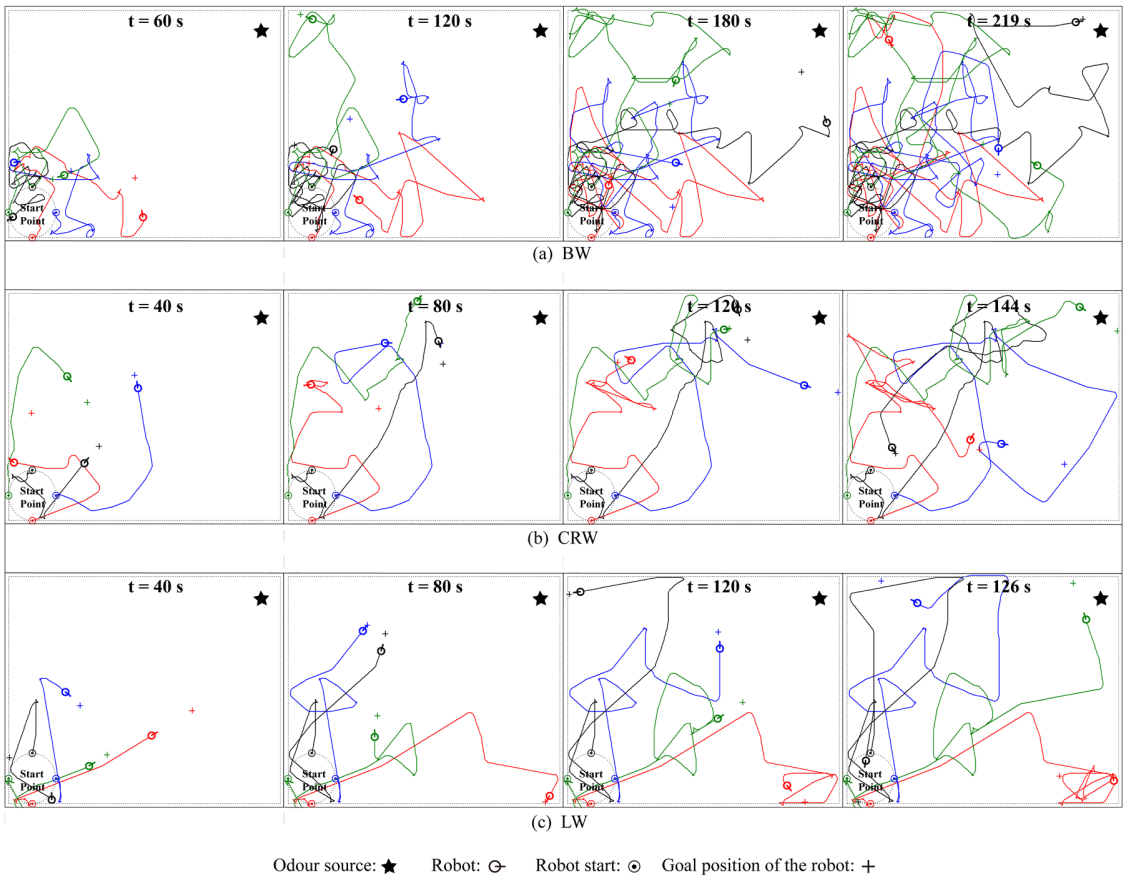

Figure 5: Robotic trajectories obtained using BW, CRW, and LW.

To further investigate the search processes, typical robotic trajectories obtained at different time points by BW, CRW, and LW are displayed in Fig. 5-a, 5-b, and 5-c, respectively. In Fig. 5-a, most MLs are about 1 m, moreover, the robots were trapped at the beginning stage in areas around the start point. This is because the robots started from the corner and most new goal positions generated using BW were repeatedly constrained by the left boundary of the VSR at the beginning. Even when the robots got into the central area of the VSR, the robots often return to the areas that have been passed by. In Fig. 5-b and 5-c, the search processes were seldom affected by the boundaries of the VSR. It is readily seen that several MLs much longer than 1 m were generated using CRW and LW in Fig. 5-b and 5-c, respectively. The robots in Fig. 5-b appear to search along more or less the same direction, while those in Fig. 5-c tend to search in individual separated areas. Therefore, the trajectories in Fig. 5-b were more overlapped than those in Fig. 5-c.

From the above experimental results, it can be deduced that DP is important for random search strategies to improve the search efficiency. Once the robot moved for a long distance along entirely or nearly the same direction, i.e., DP emerged, it usually got into a new area that is far from the visited area, and thus avoided being trapped or repeatedly searching within the visited areas. Moreover, it can be inferred that making

the robots search within different areas can improve the search efficiency. As mentioned, DP is realized in CRW and LW by controlling the distribution of TAs and MLs, respectively. In our experimental setup, the initial heading of the robots were equally distributed within an angle span of 90 degrees. Thus, the WCD in CRW, which generated TAs around 0 degree, caused the robots searching near each other. On the other hand, the uniform distribution of TAs in LW tends to make the robots leave each other. The higher time-efficiency of LW than CRW can be tentatively attributed to the higher diversity of robot positions during the search process.

5. Conclusions

We have implemented three random search strategies, i.e., BW, CRW, and LW, in a multi-robot system for finding environmental odours. BW is a typical uncorrelated random search strategy. As two correlated ransom search strategies, CRW and LW incorporate DP by controlling the probability distribution of TAs and MLs, respectively. With the help of DP, CRW and LW yielded higher time-efficiency than BW. The robotic trajectories obtained by CRW are more overlapped than those obtained by LW. Consequently, the time-efficiency of multi-robot odour finding is higher for LW than for CRW.

Acknowledgements

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References

Bartumeus, F., da Luz, M.G.E., Viswanathan, G., Catalan, J., 2005. Animal search strategies: a quantitative random-walk analysis. Ecology 86, 3078-3087.

Cao, M.-L., Meng, Q.-H., Wang, J.-Y., Luo, B., Jing, Y.-Q., Ma, S.-G., 2015. Learning to rapidly re-contact the lost plume in chemical plume tracing. Sensors 15, 7512-7536.

Jing, Y.-Q., Meng, Q.-H., Qi, P.-F., Zeng, M., Li, W., Ma, S., 2014. Electronic nose with a new feature reduction method and a multi-linear classifier for Chinese liquor classification. Review of Scientific Instruments 85, 1-10.

Li, F., 2009. Multi-robot odour-source localization in turbulence dominated airflow environments, School of electrical engineering and automation. TIanjin University, Tianjin.

Li, J.-G., Meng, Q.-H., Wang, Y., Zeng, M., 2011. Odor source localization using a mobile robot in outdoor airflow environments with a particle filter algorithm. Autonomous Robots 30, 281-292.

Lilienthal, A.J., Loutfi, A., Duckett, T., 2006. Airborne chemical sensing review. Sensors 6, 1616-1678.

Marjovi, A., Marques, L., 2013. Optimal spatial formation of swarm robotic gas sensors in odor plume finding. Autonomous Robots, 1-17.

Meng, Q.-H., Li, F., 2006. Review of active olfaction. Robot 28, 89-96.

Neumann, P.P., Bennetts, V.H., Lilienthal, A.J., Bartholmai, M., Schiller, J.H., 2013. Gas source localization with a micro-drone using bio-inspired and particle filter-based algorithms and particle filter-based algorithms. Advanced Robotics 27, 725-738.

Pasternak, Z., Bartumeus, F., Grasso, F.W., 2009. Lévy-taxis: a novel search strategy for finding odor plumes in turbulent flow-dominated environments. Journal of Physics A: Mathematical and Theoretical 42, 434010.

Odour prediction model using odour activity value from pharmaceutical industry

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Data was collected from three pharmaceutical industries (two Western pharmaceutical industries and one traditional Chinese pharmaceutical industry). Odour concentration was measured by the triangular odour bag method; compounds were quantified by gas chromatography-mass spectrometry. The specific objectives were to determine which compounds contributed most to the overall odour emanating from pharmaceutical industry, and develop equations for predicting odour concentration based on compound odour activity value (OAV). OAV is defined as the concentration of a single compound divided by the odour threshold for that compound. The larger the OAV, the more likely that compound would contribute to the overall odour of a complex odour mixture. According to the OAV and regression analyses, we concluded that acetaldehyde, acetone, ethanol and NH_3 were the most likely contributors to the odour in Western pharmaceutical sites. While for the traditional Chinese pharmaceutical site, acetaldehyde, acetone, H_2S, methanal and ethanol were the most likely contributors to the overall odor. Acetaldehyde and Acetone were the compounds with the highest OAV from both Western and Chinese pharmaceutical industries. The multivariate regression analyse results showed that individual OAV was a good predictor of odour concentration for traditional Chinese pharmaceutical industry, the R^2 of the regression equations ranged from 0.85 to 0.93. While for Western pharmaceutical industry, the odour concentration predictions was poor with R^2 ranged from 0.30 to 0.65.

1. Introduction

Environmental odors are inherent parts of most industrial sites and may be the cause of an array of reactions, frequently becoming a cause of public environmental discomfort (Carmo, 2010). Offensive odors are not only a direct threat for human health and welfare, but also represent a significant contribution to photochemical smog formation and particulate secondary contaminant emission (Belgiorno et al., 2012). In recent years, much attention was paid on waste disposal facilities such as sewage treatment plant, composting plant; landfill and so on, as well as animal feeding operation plants. Pharmaceutical industry is also an important type of odour pollution source which often causes complaints by surrounding residents. But there is little study about odour characteristics from pharmaceutical industry.

There are hundreds of odorous compounds emitted from pharmaceutical industry. However, it is unlikely that each of these compounds contributes equally to the aroma of a complex odour mixture. For environment management, it is vital to determine which compounds are most responsible for an odor. One of the methods proposed for assessing the relative importance of an individual compound in a complex odour mixture is the odour activity value (OAV). The OAV is defined as the ratio of the concentration of a single compound to the odour threshold for that compound (Friedrich

Citation: Yang W., Li W., Liu B. (2015): Odour prediction model using odour activity value from pharmaceutical industry. Austrian Contributions to Veterinary Epidemiology. Vol. 8, 51-60.

and Acree, 1998; Trabue et al., 2006). The idea of numerically adding individual OAV to assess overall odour potential was initially proposed by Guadagni (1963) and later by Leffingwell and Leffingwell (1991). When studying combinations of odorants, Audouin et al. (2001) found that OAV provided a poor estimate of odour at higher intensities but was better at lower intensities. Scientists in the food and beverage industries have used OAV to assess odorants. For example, OAV has been used to determine the most important aroma contributors to meat (G rosh, 1994), coffee (Semmelroch and Grosh, 1996), white wine (Guth, 1997), cheese (Qian and Reineccius, 2003), orange juice (Plotto et al., 2004), bread (Hansen and Sc hieberle, 2005), beer (Fritsch and Schieberle, 2005).

Despite the extensive use of OAV in the study of food and beverages, there has been limited use of OAV in assessment of odorants associated with pharmaceutical field. Conceptually, the larger the OAV, the more likely that compound will contribute to the overall odour of a complex odour mixture. In this research, three pharmaceutical industries were selected as the research objects based on the analyses of the complaint case in Tianjin. We used OAV and multivariate regression techniques for prediction of odors from pharmaceutical industries.

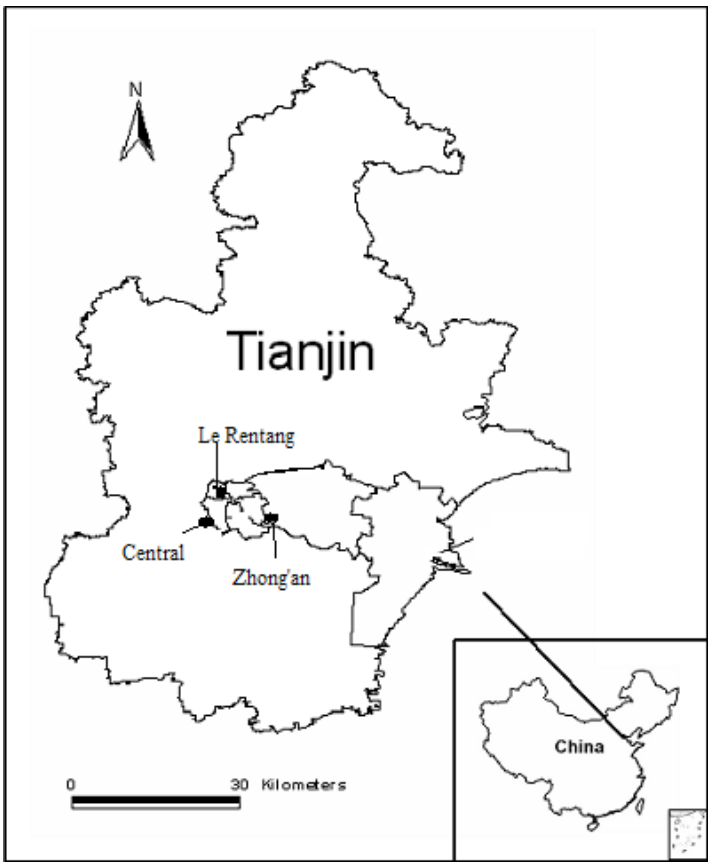

Figure 1: Localization of pharmaceutical sites in Tianjin, China.

The objectives of this study were to (1) analyze the main odorous pollutants at three pharmaceutical sites, (2) find the most significant odorants that contribute to odour concentrations of the site, (3) develop models for predicting odour concentration of pharmaceutical industries using multilinear regressions analyses compound OAV.

2. Materials and methods

2.1 Sampling sites

The study was carried out at three pharmaceutical sites located in Tianjin, China (as shown in Fig. 1). The trials took place in two different periods of the year, summer (2014) and autumn (2014), in order to guarantee the accuracy of the observation results by taking account of different meteorological conditions. Three pharmaceutical industries were selected. The sampling points were shown in Tab. 1.

Table 1: Sampling points

	Location	
ID	Western pharmaceutical industry	Traditional Chinese medicine industry
P_1	first production workshops	first extract workshop
P_2	second production workshops	second extract workshop
P_3	raw material storage	preparation workshop
P_4	first synthetic workshop	packing workshop
P_5	second synthetic workshop	exhaust funnel
P_6	iron sludge treatment	herb residue treatment
P_7	wastewater treatment	wastewater treatment

Note: For Western pharmaceutical industry sampling points, P_1, P_2, P_3 were sampled in Zhong'an pharmaceutical industry, P_4-P_7 were sampled in the central pharmaceutical industry. For traditional Chinese pharmaceutical industry, p_1-p_7 were sampled in Le Rentang pharmaceutical industry.

2.2 Experimental method

Odour concentration was measured by the triangular odour bag method. Compounds were quantified by gas chromatography-mass spectrometry. The quantitative analysis of the sample was according to EPA TO-15 method. Ammonia concentration analysis method referenced Ambient air and exhaust gas-Determination of ammonia-Nessler's reagent spetcrophotomet (HJ 533-2009). Odour analysis method based on Air quality-Determination of odor-Triangle odour bag method (GB/T14675-93).

2.3 Odour activity values

A comprehensive literature review of odour detection thresholds is presented by van Gemert (2003). The single-compound odour threshold (SCOT) is defined as the lowest concentration of a single compound in air that can be detected by the human olfactory sense when compared to a non-odorous sample (Parker et al., 2010). The concentration of the compound can be tested by gas chromatography and other analytical instruments, odour threshold can be obtained by database. Using the concentration of VOC in the air samples from three pharmaceutical industries, OAV were calculated for each individual compound. The geometric mean SCOT value was used for the calculation of OAV (eq.1):

$$OAV = \frac{C}{SCOT} \quad (1)$$

Where OAV is the odour activity value for an individual compound (dimensionless), C is the concentration of the compound (μg m^{-3}), and SCOT is the odour detection threshold for the individual compound (μg m^{-3}).

2.4 Statistcial analysis

Japanese researchers believed that compared with the odour concentration, odour index can reflect the human olfactive sensation better (Iwasaki et al., 1978). Odour concentration and odour index of the sample are calculated by eq. 2:

$$N = 10 \cdot log\ OC \quad (2)$$

Where OC=odour concentration, N=odour index.

Multilinear regressions between odour and individual gas OAV were investigated using eq. 3 (SPSS, 2008):

$$N = A_0 + A_1(OAV_1) + A_2(OAV_2) + \ldots + A_n(OAV_n) \quad (3)$$

Where OAV_1 through OAV_n are the calculated OAVs of the n individual compounds, A_0, A_1 … A_n are regression coefficients (i.e., weights applied to the OAV values) determined in the multilinear regression analyses.

Accroding to eq. 1 and eq. 2, prediction equations were also developed using multilinear regression techniques (eq. 4)

$$log\ OC = B_o + B_1(OAV_1) + B_2(OAV_2) + \ldots + Bn(OAV_n) \quad (4)$$

Where OC is odour concentration, B_0, B_1 … B_n are regression coefficients. “Backward method” were used for these analyses. The so-called “backward method” was used for these analyses. This is the most commonly used method. In the backward method, SPSS enters all independent variables into the model. Then the independent variable with the largest p-value ($p > 0.1$) is removed, and the regression is re-calculated. If this weakens the model significantly, the variable is re-entered; otherwise it is deleted. This procedure is repeated until only significant variables remain in the model.

The statistical analyses were also conducted using the MaxR (maximum R^2 improvement) selection method in SAS version 9.2 (SAS Institute, Inc., Cary, N.C.). The MaxR selection method considers all possible variable combinations to find the best (i.e., the highest R^2 per the MaxR selection method) one-variable model, the best two-variable model, the best three-variable model, and so on.

3. Results and discussion

3.1 Analyze the the main odorous compounds

For the Zhong'an pharmaceutical industry, the main odorous pollutants were inorganic gas (3.7020 mg/m^3) and organic compounds including alkane (0.3395 mg/m^3), alkene (0.0215 mg/m^3), halohydrocarbon (16.0765 mg/m^3), arene (0.1055 mg/m^3) and oxygen-containing hydrocarbon (45.3246 mg/m^3). The vast majority was oxygen-containing hydrocarbon accounting for 69.12% of the total mass concentration. There were total 40 substances quantitatively detected, containing 8 alkanes, 3 alkene, 8 arene, 10 halohydrocarbon, 9 oxygen-containing hydrocarbon and 2 inorganic gas.

For the central pharmaceutical industry, the total detection concentration was higher in summer (66.5434 mg/m^3) than that in autumn (143.3594 mg/m^3). The main odorous pollutants were inorganic gas (0.4569 mg/m^3) and organic inorganic compounds including alkane (3.8728 mg/m^3), alkene (0.6250 mg/m^3), arene (51.5933 mg/m^3), halohydrocarbon (0.1773 mg/m^3) and oxygen-containing hydrocarbon (153.1777

mg/m^3). Oxygen-containing hydrocarbon was also the vast majority accounting for 73% of the total mass concentration. There were total 55 substances quantitatively detected, including 17 alkane, 4 alkene, 14 arene, 8 halohydrocarbon, 11 oxygen-containing hydrocarbon and ammonia.

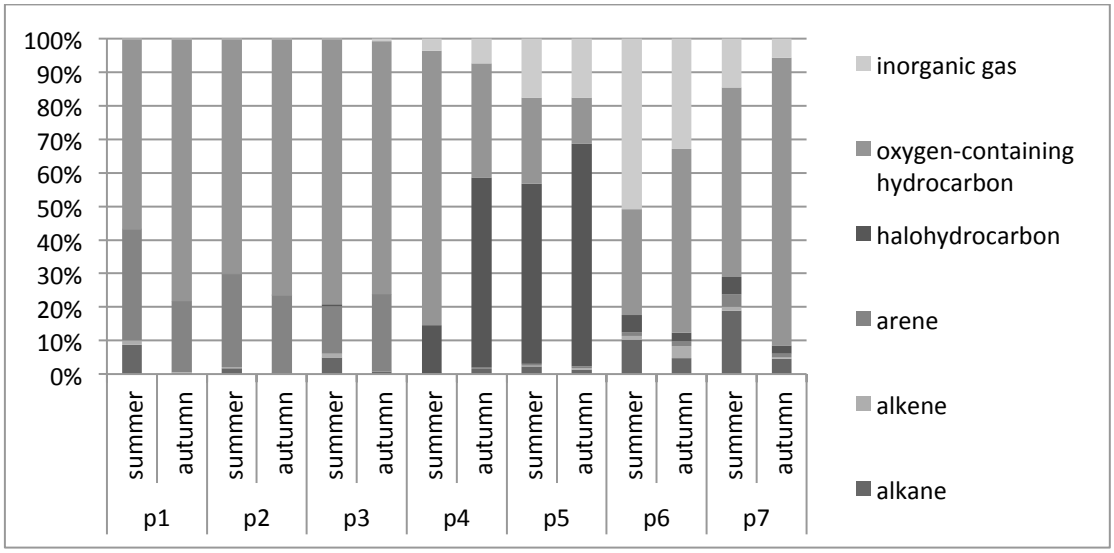

Figure 2: The proportion of pollutants concentration in Western pharmaceutical industry during summer and autumn.

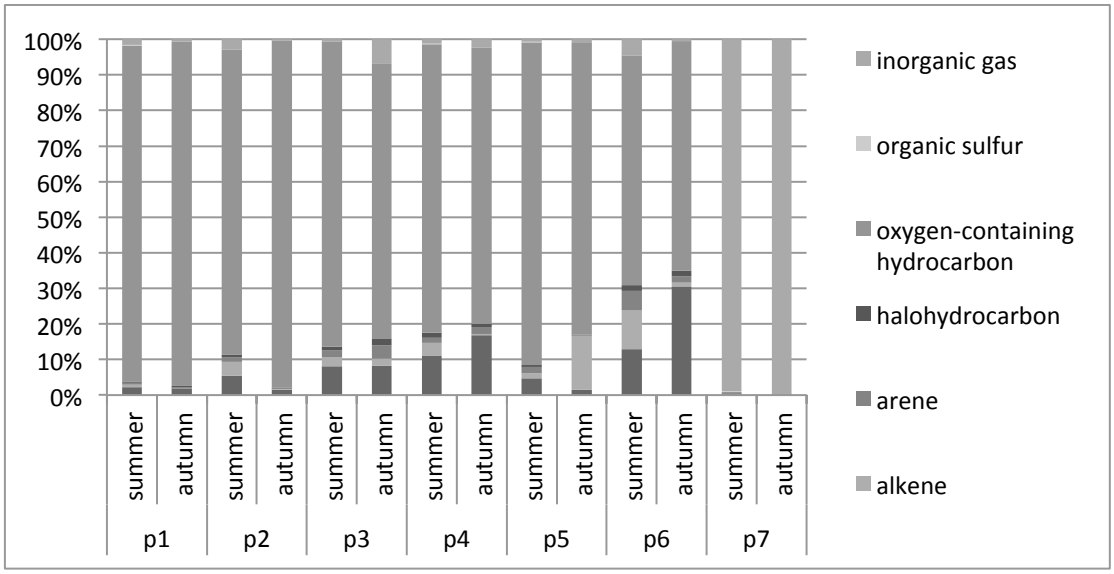

Figure 3: The proportion of pollutants concentration in Western pharmaceutical industry during summer and autumn.

Seven compounds were detected as the major contributor to total detection concentration in Le Rentang pharmaceutical industry, a maximum of 93% of the total mass concentration was attributed to oxygen-containing hydrocarbon compounds (87.1791 mg/m^3), 4% to alkane (3.6131 mg/m^3), 1% to alkene (0.7834 mg/m^3), arene (0.7455 mg/m^3) and inorganic gas (0.9255 mg/m^3), respectively, the proportion of halohydrocarbon and organic sulfur was slight. There were total 70 substances

quantitatively detected, including 17 alkane, 9 alkene, 10 arene, 17 halohydrocarbon, 14 oxygen-containing hydrocarbon, 2 inorganic gas and 1 organic sulfur.

Fig. 2 and Fig. 3 showed the proportion of pollutants concentration during summer and autumn in Western pharmaceutical industry and traditional Chinese pharmaceutical industry, respectively. It shown that the vast majority was oxygen-containing hydrocarbon compounds in both Western and traditional Chinese pharmaceutical industry. While for P_7 in traditional Chinese pharmaceutical industry, inorganic gas accounting for about 99% of the total mass concentration, it mainly due to hydrogen sulfide was the most significant compounds in wastewater treatment.

Table 2: The top three OAVs of the compounds in each site.

		Western medicine industry				traditional Chinese medicine industry			
		summer		autumn		summer		autumn	
		compound[a]	OAV	compound	OAV	compound	OAV	compound	OAV
P1	1	Acet	261.31	m-xy	18.57	Acet	610.98	Acet	935.74
	2	Ace	153.59	Ace	17.39	Ace	58.29	Ace	78.37
	3	m-xy	18.46	Acet	17.10	H_2S	26.69	H_2S	65.49
	Odour		41687		309		741		550
P2	1	Acet	170.28	Acet	177.75	Acet	624.15	Acet	933.41
	2	Ace	143.99	Buta	95.95	Prop	110.61	Isov	111.89
	3	m-xy	20.07	Acetone	62.07	H_2S	53.67	Ace	111.66
	Odour		13183		741		2344		741
P3	1	Acet	54.30	Acet	221.84	Acet	193.84	Acet	130.69
	2	Prop	49.60	Ace	63.21	Ace	62.99	Ace	20.15
	3	Acet	44.06	m-xy	4.59	Etha	3.07	Meth	0.26
	Odour		41687		417		174		174
P4	1	Prop	14765	Acet	37.57	Acet	82.33	Acet	133.63
	2	Ace	50.04	Ace	8.11	H_2S	26.41	Ace	27.89
	3	Acet	36.68	H_2S	6.51	Ace	3.93	H_2S	16.91
	Odour		132		98		417		309
P5	1	Ace	229.22	Acet	35.81	Acet	1459	Isov	18950
	2	Acet	41.67	Isov	31.01	Acet	154.75	Acet	345.26
	3	NH_3	0.48	Acet	22.84	H_2S	25.37	Ace	35.18
	Odour		234		174		1318		234
P6	1	Acet	42.17	Acet	29.63	Acet	174.68	Acet	105.86
	2	Ace	28.52	Ace	17.44	H_2S	79.68	Ace	5.26
	3	NH_3	0.73	NH_3	0.36	Ace	54.49	Meth	0.43
	Odour		977		74		550		417
P7	1	Acet	42.84	Acet	79.93	H_2S	218906	H_2S	876710
	2	Ace	21.95	H_2S	31.18	Acet	108.87	Acet	36.02
	3	NH_3	0.09	Ace	1.75	Ace	36.34	Ace	11.68
	Odour		4169		417		13183		23442

[a] Acet = acetaldehyde, Ace = acetone, m-xy = m-xylene, H_2S = hydrogen sulfide, Buta = butanone, Prop = propanal, Isov = isovaleral, Etha=ethanol, Meth = meyhanal, NH_3 = ammonia.

3.2 Single-compound odour activity value

The larger the OAV, the more likely that compound would contribute to the overall odour of a complex odour mixture. In order to compare the sensory stimulation strength of single-compound OAV and analyse their contribution, the top three OAV of the compounds were provided in Tab. 2.

The main odorous pollutants in Western pharmaceutical industry were inorganic gas and oxygen-containing hydrocarbon compounds. The compounds with highest frequency at each sampling point were acetaldehyde, acetone, followed by ethanol, ammonia. While the OAV value of ethanol and ammonia were lower, therefore, acetaldehyde and acetone were found as the most significant compounds in Western pharmaceutical industry.
For traditional Chinese pharmaceutical industry, the main odorous pollutants were inorganic gas, oxygen-containing hydrocarbon compounds, and less alkene and arene compounds. Acetaldehyde, aceton, hydrogen sulfide were found as the most significant compounds in this sampling point due to their highest frequency.
Odour concentration was found to be large difference in two seasons, the values in summer were larger than that in autumn, this was expected, odour and gas concentrations and emission rates were significantly different due to variations in the sampling point and management characteristics of the sites. It may be also due to the samples was interfered by other undetected gas compounds in summer.

3.3 Single-compound odour activity value

The multivariate regression analyses for the Western medicine industry and traditional Chinese medicine industry sites yielded numerous muli-parameter prediction models for odour concentration.
The OAV was not a good predictor of odour concentration in Western pharmaceutical industry, that is one-parameter model (Acetaldehyde only, R^2=0.30) to a 4-parameter model with R^2=0.65 (Tab. 3). The most significant compounds were Acetaldehyde, Acetone, Ethanol and NH_3. These particular compounds apparently can be used to account for up to 65% of the variance in odour concentrations. There was no serious collinearity among the independent variables. The linear regression equation was as follows:

$$\log OC = 27.262 + 0.008X_1 + 0.023X_2 + 1.652X_3 - 5.465X_4 \qquad R^2=0.65,\ P<0.05 \qquad (5)$$

Where OC was the predicted odour concentration; X_1, X_2, X_3, X_4 were the OAV of Acetaldehyde, Acetone, Ethanol, NH_3, respectively. P-value($p<0.05$) suggested the equation had a good statistical significance.
While for traditional Chinese medicine industry site, the multilinear regression results ranged from a best one-parameter model (Acetaldehyde only, R^2=0.85) to a 5-parameter model with maximum R^2=0.93 (Table 4). The most significant compounds were Acetaldehyde, Acetone, Methanol, Ethanol and H_2S. These particular compounds apparently can be used to account for up to 93% of the variance in odour concentrations. The collinearity was good among the independent variables. The linear regression equation is as follows:

$$\log OC = 29.867 + 0.007x_1 - 0.068x_2 - 8.994x_3 - 0.214x_4 - 0.001x \qquad R^2=0.93,\ P<0.05 \qquad (6)$$

Where OC was the predicted odour concentration; x_1, x_2, x_3, x_4, x_5 were the OAV of Acetaldehyde, Acetone, Methanol, Ethanol, H_2S, respectively. P-value($p<0.05$) suggested the equation had a good statistical significance.
According to these results, all correlations were statistically significant ($p<0.05$), but a maximum of 65% of the variation in odour concentrations could be predicted by using

OAV in Western medicine industry, and a maximum of 93% of the variation in traditional Chinese medicine industry. It was concluded that OAV can be used to predict odour concentrations from Pharmaceutical Industry, but these OAV will not always yield high coefficients of determination. It was mainly because odour was sampled in different site and the effect of seasonal changes on odour and gas concentrations.

Table 3: Regression coefficients and corresponding R^2 values for the model in eq. 5 (Western medicine industry site). Shown are coefficients for n = 1 to 4 parameter models.

No. of parameters	Intercept	Compound					
		Acetaldehyde	Acetone	Ethanol	NH_3	R^2	P
1	24.255	0.058	-	-	-	0.30	0.12
2	23.654	0.051	0.020	-	-	0.34	0.21
3	24.396	0.021	0.018	1.866	-	0.56	0.03
4	27.262	0.008	0.023	1.652	-5.465	0.65	0.03

Based on OAV analysis and the regression analyses, we noticed that Acetaldehyde and Acetone had the highest frequency and their OAV were higher, there was no doubt that they were the highest contributors to odour in pharmaceutical industry.

Table 4: Regression coefficients and corresponding R^2 values for the model in equation 6 (traditional Chinese medicine industry site). Shown are coefficients for n = 1 to 5 parameter models.

No. of parameters	Intercept	Compound						
		Acetaldehyde	Acetone	Methanol	Ethanol	H_2S	R^2	P
1	29.250	-4.55	-	-	-	-	0.85	0.31
2	29.311	0.001	-0.013	-	-	-	0.85	0.61
3	31.555	-0.029	-0.002	-11.162	-	-	0.92	0.00
4	36.870	0.008	-0.142	-19.315	-0.643	-	0.93	0.00
5	29.867	0.007	-0.068	-8.994	-0.214	-0.001	0.93	0.00

4. Conclusions

The following conclusions were drawn from this research:

From analyzing the total detection concentration, it shown that oxygen-containing hydrocarbon compounds had the largest proportion in both Western medicine industries and traditional Chinese medicine industry.

When odour activity values were taken into account, the most significant compounds were propanal acetaldehyde and acetone for Western pharmaceutical industry, acetaldehyde, acetone, isovaleral and hydrogen sulphide for traditional Chinese pharmaceutical industry. Both Western pharmaceutical and traditional Chinese pharmaceutical industry had the same two compounds with the highest OAVs (ranked high to low: acetaldehyde, acetone).

Although the odour concentration predictions was generally poor (R^2=0.30 to 0.65) in Western pharmaceutical industry, individual OAVs was a good predictor of odour concentration using multivariate regression analyses for traditional Chinese pharmaceutical industry (R^2=0.85 to 0.93).

Based on the OAV and regression analyses, we concluded that acetaldehyde, acetone, ethanol and NH_3 were the most likely contributors to the Western pharmaceutical sites. While for the traditional Chinese pharmaceutical sites, acetaldehyde, acetone, H_2S, methanal and ethanol were the most likely contributors.

Acknowledgment

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References

Akdeniz, N., L. D. Jac obson, B. P. Hetchler, S. D. Bereznicki, A. J. Heber, J. A. Koziel, L. Cai, S. Zhang, and D. B. Parker. 2012b. Odor and odorous chemical emissions from animal buildings: Part 4. Correlations between sensory and chemical measurements. Trans. ASABE 55(6): 2347-2356.

Ambient air and exhaust gas-Determination of ammonia-Nessler's reagent spetcrophotometry, HJ 533-2009 (In Chinese).

Audouin, V., F. Bonnet, Z. M. Vi ckers, and G. A. Reineccius. 2001. Limitations in the use of odor activity values to determine important odorants in foods. In Gas Chromatography-Olfactometry: The State of the Art, 156-171. J. V. Leland, P. Schieberle, A. Buettner, and T. E. Acree, Eds. New York, N.Y.: Oxford University Press.

Bereznicki, S. D., A. J. Heber, N. Akdeniz, L. D. Jacobson, B. P. Hetchler, K. Y. Heathcote, S. J. Hoff, J. A. Koziel, L. Cai, S. Zhang, D. B. Parker, E. A. Caraway, T. T. Lim, E. L. Cortus, and R. B. Jacko. 2012. Odor and odorous chemical emissions from animal buildings: Part 1. Project overview, collection methods, and quality control. Trans. ASABE 55(6): 2325-2334.

Carmo G.N.D., Belli P., Lisboa H.D., Schirmer W.N., Lacey, M.E.Q., 2010, Odor assessment tools and odor emissions in industrial processes, Acta Scientiarum-Technology, 32, 287-293, DOI: 10.4025/actascitechnol.v32i3.4778.

Friedrich, J. E., T. E. Acree. 1998. Gas chromatograph olfactometry (GC/O) of dairy products. Intl. Dairy J. 8(3): 235-241.

Fritsch, H. T.and P. Schieberle. 2005. Identification based on quantitative measurements and aroma recombination of the character impact odorants in a Bavarian Pilsner-type beer. J. Agric. Food Chem. 53(19): 7544-7551.

Grosch, W. 1994. Determination of potent odourants in foods by aroma extract dilution analysis (AEDA) and calculation of odour activity values (OAVs). Flavour and Fragrance J. 9(4): 147-158.

Guadagni, D. G., R. G. Buttery, S. Okano, and H. K. Burr. 1963. Additive effect of sub-threshold concentrations of some organic compounds associated with food aromas. Nature 200(4913): 1288-1289.

Guth, H. 1997. Quantitation and sensory studies of character impact odorants of different white wine varieties. J. Agric. Food Chem. 45(8): 3027-3032.

Hansen, A., and P. Schieberle. 2005. Generation of aroma compounds during sourdough fermentation: Applied and fundamental aspects. Food Sci. Tech. 16(1-3): 85-94.

Iwasaki, T., Tokida, K., Tatsuko, F., and Yasuda, S.: A practicalmethod for assessing soil liquefaction potential based on casestudies at various sites in Japan, Proceedings of 2nd International Conference on Microzonation, San Francisco, 885–896, 1978.

Leffingwell, J.C., and D. Leffingwell. 1991. GRAS flavor chemicals: Detection thresholds. Perfumer and Flavorist 16(1): 2-19.

Monitoring of Air and Exhaust Odor, Olfactory Distinguish Members Triangle Odor Bag Method, GB/T14675-93(In Chinese).

Parker, D. B., J. A. Koziel, L. Cai, L. D. Jacobson, N. Akdeniz, S. D. Bereznicki, T. T. Lim, E. A. Caraway, S. Zhang, S. J. Hoff, A. J. Heber, K. Y. Heathcote, and B. P. Hetchler. 2012. Odor

and odorous chemical emissions from animal buildings: Part 6. Odor activity value. Trans. ASABE 55(6): 2357-2368.

Plotto, A., C. A. Margaria, K. L. Goodner, R. Goodrich, and E. A. Baldwin. 2004. Odour and flavor thresholds for key aroma components in an orange juice matrix: Terpenes and aldehydes. Flavour and Fragrance J. 19(6): 491-498.

Qian, M., and G.A. Reineccius. 2003. Quantification of aroma compounds in Parmigiano Reggiano cheese by a dynamic headspace gas chromatography-mass spectrometry technique and calculation of odor activity value. J. Dairy Sci. 86(3): 770-776.

Semmelroch, P., and W. Grosch. 1996. Studies on character impact odorants of coffee brews. J. Agric. Food Chem. 44(2):537-543.

SPSS. 2008. Statistics 17.0.1 User's Guide. Chicago, Ill.: SPSS, Inc.

Trabue, S. L., J. C. Anhalt, and J. A. Zahn. 2006. Bias of Tedlar bags in the measurement of agricultural odorants. Environ. Qual. 35(5): 1668-1677.

Belgiorno, V. Naddeo , T. Zarra (Eds.),Odor impact assessment handbook, Wiley (2012).

van Gemert, L. J. 2003. Odor Thresholds: Compilations of Odor Thresholds in Air, Water, and Other Media. Utrecht, The Netherlands: Oliemans Punter and Partners.

Impressions

Biao Sun, Yi Wu, Ji-Gong Li, Jiayin Li, Qinghao Meng, Weifang Li, Günther Schauberger, Martin Piringer, Jingjing Fang, Chuandong Wu, some students (from left to right)

Photo courtesy of Yuteng Wei

Jingjing Fang

Martin Piringer, Günther Schauberger, Chuandong Wu, Qinghao Meng

Photo courtesy of Yuteng Wei

Qinghao Meng, Weifang Li, Jingjing Fang

Martin Piringer

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Chuandong Wu


Qinghao Meng

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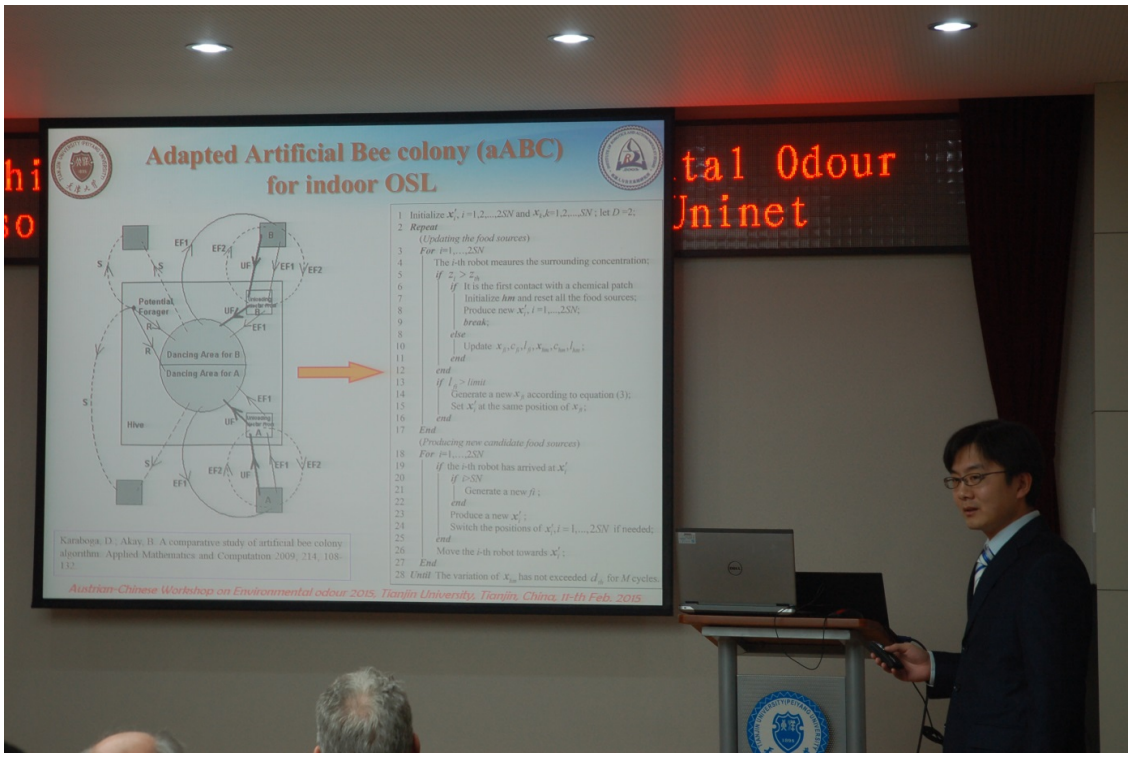

Mengli Cao

Ji-Gong Li

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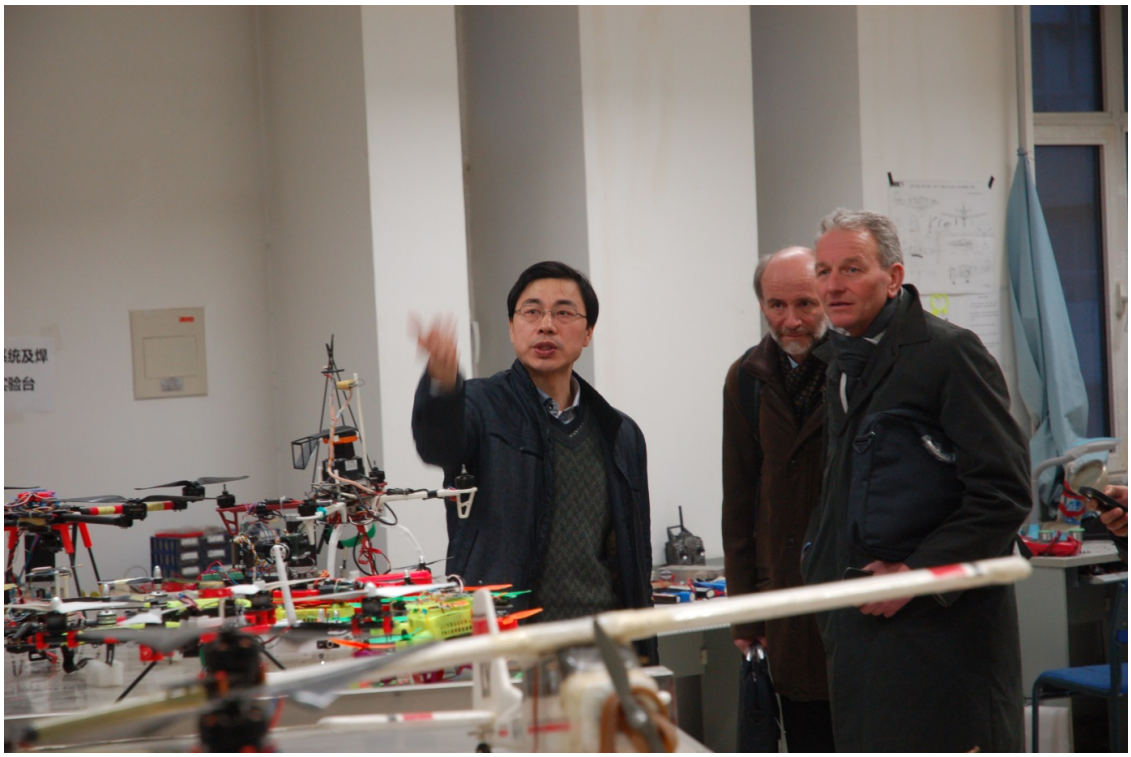

some robots …, Qinghao Meng, Martin Piringer, Günther Schauberger

Weifang Li, Jingjing Fang, Ji-Gong Li

Photo courtesy of Yuteng Wei

Martin Piringer, Qinghao Meng, Weifang Li, Jingjing Fang, Jiayin Li, Biao Sun, Yi Wu, Chuandong Wu, Ji-Gong Li (clockwise at the table)

Günther Schauberger, Martin Piringer, Qinghao Meng, Weifang Li

Photo courtesy of Yuteng Wei

Ji-Gong Li, Chuandong Wu, Qinghao Meng, Martin Piringer, Günther Schauberger

Ji-Gong Li, Martin Piringer, Qinghao Meng, Günther Schauberger

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Austrian Contributions to Veterinary Epidemiology

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1	Rubel, F., 2005: Prozessmodelle in der Veterinär-Epidemiologie (ISBN 3-9502042-0-2)	14,-
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