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Enhancement of the Sensory Capabilities of Mobile Robots through Artificial Olfaction

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ENHANCEMENT OF THE SENSORY CAPABILITIES OF MOBILE ROBOTS
THROUGH ARTIFICIAL OLFACTION

Realizada bajo la dirección de Javier González Jiménez y Javier González Monroy.

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Enhancement of the Sensory Capabilities of Mobile Robots through Artificial Olfaction

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Nothing is impossible.

For eons, we have witnessed how the Sun and the Moon
chase after each other in an endless dance.
A romance never meant to happen.
A love story never to be told.

But long after the time of man has passed,
the heart of the Sun will turn into iron
and its shell of plasma will expand
like longing tendrils of fire.
Meanwhile, all planets and moons in the system
will have grown tired of their orbits.
Slowly bleeding their energies
into tidal forces that feed entropy.
Then too, will the Moon fall toward the Sun.

And so, on the very last day,
the impossible will happen.
There will be no gods.
There will only be reunion.

46 6F 72 20 41 65 6E 65 61

Contents

Abstract

This thesis takes a broad approach to olfactory robotics, covering from the required gas-sensing hardware to some of the main applications of olfaction-enabled robots. In the first place, we discuss the design of an e-nose that is specifically meant for mobile robots, but that can also be operated manually to facilitate experimentation. Then, we take an alternative approach to gas source localization (GSL), first under simulation and later by equipping a robot with the aforementioned electronic nose. We substitute the autonomous component of GSL with more mature teleoperation technologies, so that we may experimentally assess whether a human-controlled robot can find gas sources with limited sensor data and how this is accomplished. Afterward, we present a novel mathematical model for gas distribution mapping (GDM) that allows a robot to estimate gas distributions with very few observations. The main property of our method is that it estimates the wind in the environment along with the gas distribution, so that it can exploit their strong physical correlation to provide more reliable maps for both magnitudes. Finally, we also address artificial smell-recognition, understood as the ability to recognized and draw semantic meaning from aromas with an electronic nose, and which could potentially allow for many new applications for a robot equipped with it. All contributions of this thesis have been validated experimentally, and so it also includes two datasets of human-driven GSL (one simulation and one real-world setup), a stringent comparison of indoor GDM methods, and a labeled dataset of smells detected with our electronic nose.

Acknowledgments

Pursuing a Ph.D. has been a daunting experience. I have come a very long way since I started, and although there were many valleys to this path, I am also happy that I chose to walk it. Especially because I got to work with many interesting people, and they taught me how to look at the world from different perspectives. These people include not only mentors and coworkers, but also family and friends, all of which supported me throughout this adventure and deserve a warm mention.

I have been thinking for days of where to start and what to say. Somehow writing this part is turning out to be the hardest of the whole thesis. Yet, by overthinking this I have finally come to realize one thing. Life is but a succession of coincidences. Little happy accidents that create colorful adventures in our day-to-day, which you can not change without sacrificing the present. Every single person who has been in my life so far has in some way or another contributed to this work, be it directly or indirectly. And if you are reading this section, it is quite likely that you are one of them.

Thus, I just want to say thank you. Thank you for the late hours in the lab reinventing the wheel, for teaching me how microcontrollers work, for excelling at teaching, for being awesome class mates, friends, and roommates. Thank you for our crazy brainstorming sessions, for teaching me math, for reviewing my papers and for being passionate engineers. Thank you for being amazing hosts and co-workers, home is where you are. Thank you for all the breaks we took in the cafeteria, for the amazing stories we shared during lunch, and for your hugs when I needed them. Thank you all for being you. You know who you are.

Also, I want to express my most sincere gratitude to Prof. Dr. Javier González Jiménez. You are a model to follow of what being a passionate engineer and researcher truly is. You convinced me to pursue this Ph.D. and then supported me the times I was about to give up. Without your guidance and effort, I would have never made it. You always had time to hear me out and knew a solution to even the most complicated of situations. We at MAPIR are truly lucky to have you with us in the trenches.

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Andres Gongora
Malaga, March 2020

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Resumen

Introducción

Hoy es sábado. Pero no es un sábado cualquiera. Hoy es sábado 23 de septiembre de 2124, una fecha muy especial y no solo porque coincide con el equinoccio de otoño.

Hace apenas unos meses que terminaste tu doctorado y te mudaste a la Gran Ciudad en busca de nuevas oportunidades. Aquí vives como la mayoría de la gente, en uno de entre mil rascacielos cubierto por reclamos publicitarios. Tu estudio no es muy grande, pero tiene todo lo que necesitas y el alquiler es más que asequible teniendo en cuenta cómo están las cosas. Te mudaste aquí porque querías encontrar tu propio camino, pero sobra decir que no te viniste completamente solo. Al fin y al cabo, no eres uno de esos biorradicales. Como la mayoría de la gente, compartes piso con tu robot personal. En concreto, el mismo que tenías cuando empezaste en la universidad, aunque ya no parezca el mismo con todas las mejoras que le has instalado a lo largo de los años. Aun así, admites que es un chisme un poco viejo, de los que aún usan inteligencia emulada en lugar de matrices líquidas, pero hace buena compañía y te mantiene la casa justo como te gusta.

La razón por la que hoy es un día tan especial es porque tienes una cita. De hecho, es la primera desde que te viniste a la ciudad, así que estás el doble de nervioso por temor a meter la pata. La cita no es hasta dentro de dos horas, pero decides que es mejor esperar allí que correr el riesgo de llegar tarde y dar una mala primera impresión. Te pones tu reloj favorito, el que te regaló tu abuelo, y coges la gabardina por si vuelve a llover. Pero, antes de salir, te miras una última vez en el espejo y le preguntas a tu robot que qué tal vas.

Este se acerca con sus habituales movimientos fluidos y, mientras te coloca los hombros de la camisa un poco mejor, te dice que la nueva colonia que llevas le va a encantar a tu cita.

Ya un poco menos nervioso abres la puerta del pasillo para salir cuando, el robot aún a tu lado, te avisa de que deberías llevarte tu mascarilla activa. Ha detectado que los niveles de O_3 en el aire que acaba de entrar siguen elevados. Parece que hoy la contaminación es especialmente intensa, aunque no te habías percatado porque la unidad de acondicionamiento de tu vivienda logra mantener el aire medianamente respirable. Tu mayordomo robótico también te informa sobre el itinerario más seguro que deberías tomar si deseas andar hasta la cita por la superficie en lugar de usar los túneles subterráneos; la red de sensores de la ciudad ofrece esta información en tiempo real a todos sus ciudadanos justo para este fin. Era necesario, todos se han ajustado a las nuevas condiciones. El mundo está al borde del colapso medioambiental. Pero hoy no es un día para pensar en eso. Hoy tienes una cita.

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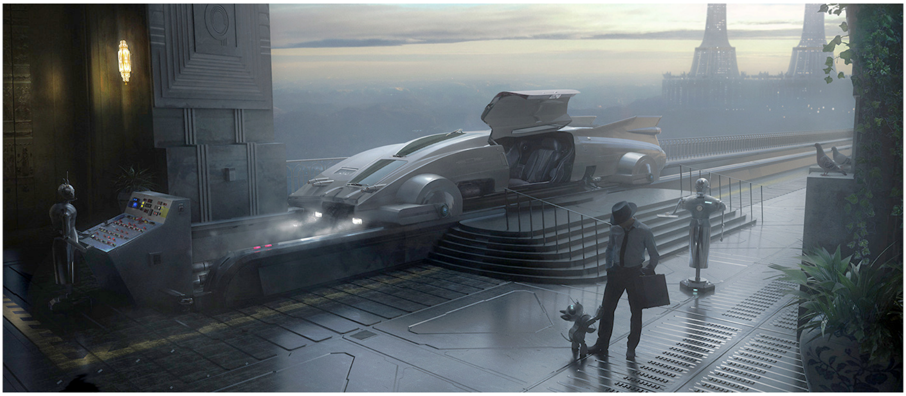

Figura 1: Puede que algún día los robots sean elementos completamente cotidianos en nuestro día a día. Ilustración de la novela gráfica *Aurora Noir*.

Tal vez esta historia contenga más ficción que ciencia, pero el futuro siempre tiene el hábito de superar todas nuestras expectativas. Si volvemos a la actualidad, cuando hablamos de robótica autónoma móvil nos referimos a la tecnología que permite a un agente mecánico interactuar de forma inteligente y autosuficiente con el entorno que le rodea, ya sea, por ejemplo, para explorar de forma reactiva un lugar desconocido, como los robots científicos submarinos, la superficie de Marte o actuar de forma proactiva en un espacio propenso al cambio, como los robots sociales que ayudan a la vida independiente de personas mayores. Pero sea cual sea la aplicación que tomemos como referencia, todas tienen una cosa en común: la necesidad de obtener información del entorno con la que poder tomar decisiones inteligentes. En este contexto, es muy habitual buscar inspiración en los seres vivos, porque ya sea para buscar alimento, detectar depredadores o comunicación con otros miembros de la especie, observamos un gran abanico de sentidos desarrollados para este fin, entre los que se incluye, aunque sea poco frecuente en robótica, el olfato.

Al dotar a un robot con la capacidad de detectar sustancias en el aire, es decir, con olfato artificial, este adquiere acceso a toda una nueva dimensión de información sobre el entorno. Por ejemplo, en los casos antes mencionados, un *rover* marciano podría detectar la presencia de gases orgánicos (p. ej. metano) acumulados en el subsuelo o un robot para asistencia a la tercera edad podría comprobar la salubridad de los alimentos del frigorífico. Otros ejemplos de aplicaciones en robótica son la detección automática de fugas de gas en plantas industriales o la aceleración en la búsqueda de supervivientes en edificios colapsados al detectar el CO_2 exhalado por las personas atrapadas. Otro ejemplo más son los robots aéreos para controlar la calidad del aire, capaces de medir la contaminación urbana a diferentes alturas y entre edificios para posteriormente decidir la mejor estrategia con la que combatirla. Por lo general, hay tantos usos para la robótica olfativa como aplicaciones en las que un robot puede beneficiarse de medir la composición del aire, independientemente de si es para aplicaciones científicas, de seguridad, biomédicas, militares u otras.

Ciertamente, esta tecnología no está tan avanzada como otros aspectos de la robótica. Al fin y al cabo, integrar olfato artificial en un robot y diseñar estrategias que hagan uso de la nueva información no es una tarea sencilla. Pero, con todas las ventajas que ofrece, es más que razonable pensar que el olfato será algún día un aspecto habitual más en cualquier robot.

Motivación

Pese a los muchos beneficios que el olfato artificial ofrece a la robótica móvil [1], aún quedan muchos elementos clave por resolver para su implantación efectiva. La primera dificultad de este campo se encuentra en los propios dispositivos encargados de adquirir información olfativa, denominados narices electrónicas. Comúnmente, las narices electrónicas están formadas por una matriz de sensores electroquímicos simples, los cuales individualmente pueden medir un gran abanico de sustancias volátiles (CO_2, CO, CH_4, etc.) pero que no ofrecen información sobre la identidad química de los mismos [2]. Por tanto, la respuesta conjunta de estos sensores es tratada como una «huella olfativa» con la que las narices electrónicas, mediante un procesado posterior, logran identificar [3, 4] y/o cuantificar [5, 6] aromas y gases. En sí, este concepto no es nuevo y existen desde hace tiempo narices electrónicas comerciales [1] Dependiendo del uso para el que estén previstas, suelen ser dispositivos pesados y caros que están diseñados para precisión (i. e. instrumentos de laboratorio) o, por el contrario, son muy compactos y ligeros (i. e. portátiles) pero solo pueden detectar ciertos gases muy específicos [7, 8]. Aun así, apenas existen versiones que sean aptas para robótica olfativa, la cual requiere que las narices electrónicas sean simultáneamente fáciles de transportar (la mayoría de los robots pueden llevar un peso muy limitado) y sensibles a un gran abanico de sustancias genéricas (similar al olfato de un mamífero). Reunir estas características es un importante desafío para el estado del arte actual pero, sin un dispositivo así, la robótica olfativa no puede alcanzar todo su potencial.

Otra limitación en la robótica olfativa se debe a la dificultad intrínseca de trabajar con gases. Las narices electrónicas convencionales, como las arriba descritas, requieren de contacto físico con la sustancia de interés y, por tanto, no pueden medir a distancia. En consecuencia, cualquier robot equipado con estas narices electrónicas solo puede obtener medir en su posición actual e incluso con ventiladores o bombas de aire [9], el aire que está inmediatamente alrededor. Esto puede suponer un inconveniente si la función del robot es explorar para detectar la presencia de gas (por ejemplo, para activar una alarma), pero es una limitación importante para aplicaciones en las que el robot también necesite conocer el gradiente o contorno de la distribución. La capacidad sensorial del robot no le permite percibir la distribución completa de forma instantánea, pero ir a medir en cada posición del entorno puede ser

[1] En nuestro día a día estamos rodeados de sensores, tanto en nuestro teléfonos móviles y relojes inteligentes como cada vez más en nuestros hogares (domótica) y ciudades conectadas (redes de sensores). Pero, pese a que la primera versión de la nariz electrónica se propuso en 1982 [3], esta tecnología de sensores sigue relegada al ámbito académico y a industrias muy especializadas, como refleja el desconocimiento de las mismas por la mayoría de la gente. Sin duda, se están produciendo grandes avances en el ámbito de las narices electrónicas, pero se trata de una tecnología que acaba de empezar a coger fuerza.

excesivamente costoso o incluso imposible [2]. La única solución es diseñar una estrategia que se adapte a los sensores del robot para medir de forma eficiente a la vez que se mantiene la precisión requerida, como, por ejemplo, en el caso de dos de las aplicaciones más importantes para la robótica olfativa [13], a saber, la búsqueda de fuentes de gas (BFG) y la estimación de mapas de distribución de gas (MDG).

- **BFG** comprende todas las tareas en las que el robot deba encontrar el origen de una sustancia volátil concreta [14, 15], como, por ejemplo, buscar fugas de gas en zonas de difícil acceso, lo cual es de especial interés para aplicaciones relacionadas con seguridad industrial [16, 17, 18, 19, 20] y ha motivado numerosos proyectos de investigación [21]. Pero, pese a todos los esfuerzos, aún no existe una solución satisfactoria para entornos genéricos y no controlados [13, 22, 23]. Hasta ahora, la naturaleza caótica de los gases [24] ha limitado este tipo de aplicaciones a situaciones relativamente simples (i. e. condiciones de viento constante y laminar [14, 25], ausencia de obstáculos [26, 27], sobrespecialización a un único entorno [28], etc.) que no son representativas de la realidad. Aunque el concepto de BFG es muy simple, aún no existe una estrategia de búsqueda eficiente. Lo único que sabemos con seguridad es que, en la práctica, es factible con sensores locales como las narices electrónicas, ya que la mayoría de los animales pueden rastrear un olor incluso en condiciones adversas.

- **MDG** busca generar un mapa de la distribución espacial en el entorno de un determinado gas sin necesidad de medirlo en todas partes, como, por ejemplo, para estudiar la calidad del aire en cada zona [29, 30]. Para ello, los robots deben extrapolar la intensidad del gas a las posiciones no visitadas pero, dado que sus recursos suelen ser muy limitados y suelen necesitar la información en tiempo real, no pueden recurrir a simulaciones precisas pero costosas basadas en mecánica de fluidos computacional. Por tanto, el estado del arte actual para la generación de estos mapas solo contempla espacios simples con pocos o ningún obstáculo [31, 32], aplicaciones en las que la extrapolación se realiza solo de forma local [33] o técnicas que no tienen en cuenta el efecto del viento sobre el gas a la hora de hacer la estimación [34], lo cual deja mucho margen para mejoras

[2] Esta limitación también se aplica a sensores basados en espectroscopia de absorción de un haz láser [10], conocidos como sensores TDLAS por sus siglas en inglés. Aunque esta tecnología tiene la ventaja de poder medir gas a distancia (en el ejemplo anterior, un robot equipado con TDLAS puede detectar gas con mayor facilidad para activar una alarma), tampoco puede percibir la distribución de gas en el entorno de forma inmediata. Dado su principio de funcionamiento, el valor medido es siempre la concentración total a lo largo de todo el haz láser. Esto significa que, para conocer la concentración en un único punto, hay que observarlo desde todos los ángulos posibles para calcular su valor real sin que le afecte la concentración de gas de las demás posiciones circundantes [11, 12].

en el futuro, siempre y cuando el mapa se pueda seguir calculando en el robot.

Finalmente, la última carencia en la robótica olfativa se encuentra en la capacidad del robot de interpretar de forma subjetiva los olores que detecta. Es decir, la capacidad de identificar con su nariz electrónica un aroma genérico en el ambiente y convertirlo en información útil para su tarea. En sí, esta limitación está más arraigada a las narices electrónicas que a las capacidades del robot, ya que únicamente depende del posprocesado de la matriz de sensores de la misma. No obstante, es un requisito indispensable tanto para que los robots puedan realizar tareas complejas en las que necesitan identificar olores como para que puedan comunicarlos a humanos en términos comprensibles para ambos. Por ejemplo, hay aplicaciones en las que una nariz electrónica es capaz de reconocer vinos [35] o aceites de oliva [36] con gran precisión, pero los clasifica mediante unos descriptores abstractos que no tienen relación con conceptos intuitivos como la acidez o dulzura de los mismos. En contraposición, la solución ideal sería que los robots pudiesen percibir los olores de la misma manera que nosotros, pero con la ventaja añadida de también detectar sustancias inodoras como el CO_2 o el vapor de agua. Es decir, que los robots pudiesen *oler* los gases que miden con sus narices electrónicas, permitiéndoles reconocer si alguien lleva demasiada colonia, como en la introducción de esta tesis, o tomar las medidas pertinentes si detectan sustancias nocivas en el aire.

Contribución

Esta Tesis Doctoral aborda de forma transversal el campo de la robótica olfativa a fin de superar algunas de las limitaciones antes descritas. Para ello, la presente busca, en primer lugar, el desarrollo de una nariz electrónica que esté diseñada específicamente para ser integrada en robots móviles pero que, a fin de facilitar la investigación, también se pueda operar manualmente. Una vez desarrollado el dispositivo, nos centramos en la búsqueda de fuente de olores mediante robots teleoperados. Esto supone una alternativa efectiva para situaciones en las que un robot autónomo no lograría encontrar el origen del olor, a la vez que nos permite estudiar el comportamiento de búsqueda humano para el desarrollo de futuros algoritmos eficientes. También abordamos la estimación de mapas de gas con esta nariz electrónica. Hemos desarrollado un nuevo método con el que, al combinar en cada momento la información disponible sobre gas, viento y obstáculos, logra calcular mapas fiables para entornos muy complejos. Además, hemos ampliado este método con los conocimientos adquiridos durante nuestros trabajos con teleoperación para desarrollar una solución para mapeado de gases completamente autónoma.

Con nuestro algoritmo, un robot puede crear de forma automática un mapa de los gases en su entorno, eligiendo para ello la ruta de exploración que más información proporcione en todo momento. Finalmente, también presentamos una pequeña contribución al tema de «oler con robots», en la que comparamos la respuesta de la nariz electrónica con la percepción humana para el reconocimiento automático de los olores urbanos y productos químicos. Las contribuciones de esta tesis pueden dividirse en los siguientes cuatro temas principales.

Contribución a las Narices Electrónicas

Nuestro primer trabajo, presentado en [8], busca diseñar una nariz electrónica que se adapte a los requisitos de la robótica móvil, específicamente en lo que se refiere a la portabilidad del dispositivo (i. e. peso, consumo, dimensiones) frente al número de sensores y variedad de aromas que puede reconocer. Idealmente, una nariz electrónica así debería sobresalir en ambas propiedades simultáneamente, lo que permitiría incluso a robots pequeños detectar todo tipo de sustancias. Pero, dadas las características técnicas y dimensiones de los transductores de gas actuales [37], lo normal es que los diseños deban favorecer una frente a la otra. Por un lado, hay que tener en cuenta que existe una gran variedad de sensores que pueden emplearse en una nariz electrónica, cada una con sus propias ventajas y desventajas en términos de gases detectables, sensibilidad y tolerancia a factores ambientales (p. ej. humedad, temperatura), entre otros [2], sin que ninguna sea claramente superior a las demás. Mientras que, por otro lado, cada aplicación puede requerir un conjunto de estos sensores completamente diferente según los aromas de interés, pero integrarlos todos en una única nariz electrónica impediría que esta fuese fácil de transportar. Así pues, en lugar de limitarnos a un único diseño capaz de alcanzar este difícil equilibrio, contribuimos en esta tesis con una arquitectura modular capaz de adaptarse a un amplio rango de especificaciones.

Nuestra nariz electrónica está formada por nodos: módulos electrónicos autocontenidos e inteligentes que pueden comunicarse de forma descentralizada. Cada nodo contiene uno o más sensores y se ocupa de la gestión completa de los mismos, enviando sus mediciones de gas por un puerto compartido para alimentación y datos, lo que también permite la integración de nodos con funciones auxiliares, como por ejemplo GPS para geolocalizar las medidas de gas o Bluetooth para comunicaciones inalámbricas. De esta forma, en lugar de disponer de un conjunto predeterminado de sensores, podemos ensamblar narices electrónicas con la combinación que mejor se ajuste a la aplicación prevista tanto añadiendo como eliminando sensores, lo cual reduce considerablemente el tiempo de desarrollo para situaciones en las que aún no se sabe qué combinación de sensores es óptima.

Contribución a la Búsqueda de Fuentes de Gas

Pese a numerosos esfuerzos por encontrar una solución satisfactoria, los algoritmos actuales para BFG no son aptos para entornos genéricos y complejos [13]. Así que, en lugar de diseñar un algoritmo nuevo más, hemos dado un paso atrás y enfocado el problema desde una perspectiva diferente: en vez de con robots autónomos, abordamos el problema mediante teleoperación. Esto conserva la capacidad del robot para acceder y medir gas en lugares potencialmente peligrosos, pero reemplaza su *inteligencia* por la del operador [38] para tomar decisiones más difíciles. Evidentemente, nuestro enfoque sacrifica algunas de las ventajas que ofrecen los robots totalmente autónomos pero, a cambio, nos permite afrontar situaciones que, de otra forma, aún no serían viables y, sobre todo, nos brinda una nueva herramienta para estudiar los requisitos imprescindibles para la BFG.

Sabemos que los seres vivos, humanos incluidos, podemos seguir un olor hasta su origen con relativa facilidad. De forma intuitiva, la clave parece estar en la combinación del olfato con nuestros otros sentidos (p. ej. visión, percepción de la dirección del viento, etc.). Pero al menos igual de importante es cómo utilizamos esta información para dirigir nuestra búsqueda de forma reactiva. Por tanto, uno de nuestros objetivos es obtener una mejor comprensión del comportamiento de búsqueda de gases en humanos y, más específicamente, cuándo la información sensorial está limitada a la del robot. Es decir, queremos estudiar si los sensores de un robot son suficientes para BFG cuando el robot es teleoperado y, en caso afirmativo, cómo es la estrategia empleada por los operarios para localizar la fuente.

Con este fin presentamos tres publicaciones en esta Tesis Doctoral. En nuestro primer trabajo [39] realizamos un experimento con un robot simulado en el que los operarios (voluntarios sin experiencia previa) debían encontrar una fuente de gas mientras registrábamos todos los datos para un análisis posterior. Al tratarse de simulación, pudimos asegurar condiciones iniciales idénticas a la vez que realistas [40] para cada experimento, los cuales se realizaron con diferentes distribuciones representativas de situaciones típicas. Para probar la relevancia de los sensores con cuatro niveles de dificultad, añadíamos al robot de forma incremental (i) una nariz electrónica, (ii) un anemómetro, (iii) un mapa de concentración de gases predictivo [41] e (iv) indicadores visuales en las posiciones de interés. Respecto a estos últimos, queremos resaltar que los operarios tenían en todo momento acceso a una cámara para dirigir al robot, pero que solo en esta combinación se añadían tuberías virtuales al entorno para indicar los posibles orígenes del gas. El resultado del trabajo fue una base de datos con más de 150 experimentos de 69 participantes cuyo análisis se llevó a cabo en una segunda publicación [42]. Como era de esperar, los experimentos en los que los usuarios disponían de todos los sensores obtuvieron la mejor tasa de éxito. No obstante, la mayoría de los otros experimentos también lograron encontrar la fuente incluso cuando solo se usaba la nariz electrónica y no se observó correlación entre eficiencia en la búsqueda (tiempo y esfuerzo necesario) y éxito de la misma. Esto es un resultado interesante porque, como luego confirmamos mediante experimentos reales en nuestro tercer trabajo [43], la estrategia de búsqueda empleada por los operarios difiere de un seguimiento de plumas de olor tradicional. En su lugar, el comportamiento observado se asemejaba a lo que se conoce en la literatura como *infotaxis* [44], la obtención de información del entorno desde una perspectiva probabilística. Es decir, los operarios no buscaban el origen del olor de forma directa, sino que exploraban el entorno para acotar iterativamente áreas de interés hasta, finalmente, quedarse con el lugar más probable.

Contribución a la Estimación de Distribución de Gases

En el trabajo presentado en [45] nos centramos en MDG, esto es, estimar la concentración de gas en lugares en los que el robot aún no ha medido para generar un mapa completo. Para ello hemos desarrollado un modelo matemático que explica cómo el gas se distribuye entre posiciones adyacentes según las condiciones de viento y obstáculos y cómo estos valores afectarían a las medidas de una nariz electrónica. Entonces, al usar este modelo en una estimación *maximum a posteriori*, el robot puede calcular «a la inversa» la distribución de gas completa que mejor explica las observaciones que haya hecho hasta el momento.

La ventaja de nuestro trabajo frente a otras técnicas similares radica en que también modelamos, junto al gas, las corrientes de viento del entorno, lo que reduce considerablemente el número de posiciones individuales en las que hay que medir para obtener un mapa fiable. Por ejemplo, si el robot sabe que hay un pasillo muy largo con una entrada y una salida, con medir en uno de los extremos ya puede estimar el otro. Al fin y al cabo, si gas y viento entran por un lado, necesariamente han de salir por otro. Adicionalmente, como nuestro modelo utiliza una formulación probabilística, a cada posición del mapa se le asigna una incertidumbre individual. Las posiciones que están cercanas a las observaciones del robot obtienen una incertidumbre relativamente baja, mientras que aquellas que están alejadas o en espacios aislados reciben una alta. Esto permite al robot decidir si tiene suficiente información antes de realizar una acción o si debe continuar explorando para cumplir con los objetivos de su tarea.

Posteriormente, en un segundo trabajo [46], adaptamos nuestro método MGD para su uso con robots completamente autónomos. Nuestro objetivo es permitir que éstos puedan elegir la ruta óptima a lo largo de la cual tomar medidas sin necesidad de intervención externa, es decir, que el proceso MDG en su conjunto sea automático. Para ello sabemos de nuestros experimentos anteriores con teleoperación que cualquier estrategia a tal efecto debe centrarse en maximizar la información adquirida sobre el entorno, o en otras palabras, *infotaxis*. Así pues, proponemos un algoritmo en el que en cada instante, el robot estima un hipotético mapa de gas para todas las rutas alternativas que podría tomar en su futuro próximo, y lo compara con su mapa actual para determinar cuál de las opciones aportaría el mayor incremento en información. También tiene en cuenta la energía y tiempo requerido por cada una antes de elegir la óptima, y para evitar un comportamiento de exploración demasiado voraz, mantiene un equilibrio razonable entre seguir midiendo cerca de zonas ya exploradas para mejorar su fiabilidad frente explorar áreas nuevas en busca de gas. El resultado es un algoritmo que puede entenderse como estimación de mapas de distribución de gas guiada por información, o IGDM de sus siglas en inglés, y que permite a un robot ajustar su exploración en tiempo real a medida que éste adquiere nuevas medidas de gas y viento.

Contribución al Reconocimiento de Olores Mediante Olfato Artificial

En este último grupo de contribuciones, presentadas en [47, 48], tratamos el reconocimiento de olores mediante olfato artificial. Buscamos asociar la respuesta sensorial de una nariz electrónica a la percepción subjetiva humana, de tal forma que los aromas que el dispositivo detecte se puedan identificar mediante etiquetas intuitivas (p. ej. floral, tabaco, basura) para facilitar la comunicación entre robots y humanos. La principal dificultad en este aspecto es la complejidad de la respuesta de los sensores ante incluso las sustancias aromáticas más simples, por lo que una asociación directa con el aroma no es posible. La única solución es entrenar a la nariz mediante aprendizaje por computación, pero para ello hace falta un conjunto de datos de entrenamiento suficientemente grande en los que se relacione la respuesta de la nariz con el nombre de cada olor.

En el primero de los dos trabajos [47] nos centramos en obtener precisamente estos datos de entrenamiento y en procesarlos. Para ello, hemos empleado una configuración *wearable* ultraportátil de nuestra nariz electrónica que, junto a una aplicación para teléfonos móvil, permite al portador registrar todos los olores que se encuentra en su día a día. El resultado es un registro con más de 10 horas de medición continua y más de 600 registros únicos de 16 olores típicos (p. ej. tabaco, basura, flores, comida, etc.). Así mismo, también estudiamos la mejor opción para entrenar a un clasificador de olores con los datos obtenidos. De entre las siete técnicas de aprendizaje por computador probadas, nuestros resultados muestran que las *redes neuronales convolucionales*, o *Deep Learning*, proporcionan los resultados más fiables. Finalmente, y como demostración conceptual, utilizamos la nariz electrónica entrenada junto a un GPS para generar automáticamente mapas de olores de nuestra ciudad en los que se indica la presencia de aire fresco, olores desagradables causados por tráfico y otro tipo de aromas.

En nuestro segundo trabajo [48] utilizamos un enfoque muy similar, pero esta vez para discernir entre olores urbanos genéricos y gases nocivos causados por un vertido químico en Coria del Río, Sevilla. En esta ocasión, empleamos una configuración de la nariz electrónica con succión de aire para acelerar su tiempo de respuesta y añadimos a la *red neuronal convolucional* una etapa previa de compensación por humedad y temperatura. El objetivo de este diseño es mejorar la fiabilidad de las predicciones, dado que se trataba de una situación que afectaba a varios vecinos. El resultado fue un mapa de los gases en el área afectada que permitió al ayuntamiento de la localidad valorar el correcto funcionamiento de las medidas paliativas instaladas.

Publicaciones

La presente tesis recoge las siguientes publicaciones:

Revistas

- *Andres Gongora, Javier Monroy y Javier Gonzalez-Jimenez.* **An Electronic Architecture for Multi-Purpose Artificial Noses.** Journal of Sensors (2018).

- *Andres Gongora y Javier Gonzalez-Jimenez.* **Olfactory Telerobotics. A Feasible Solution for Teleoperated Localization of Gas Sources?** Robotics and Autonomous Systems (2019).

- *Andres Gongora, Javier Monroy y Javier Gonzalez-Jimenez.* **Joint Estimation of Gas & Wind Maps for Fast-Response Applications**. Applied Mathematical Modelling (2020).

- *Andres Gongora, Faezeh Rahbar, Chiara Ercolani, Javier Monroy, Javier Gonzalez-Jimenez, and Alcherio Martinoli.* **Information-Driven Gas Distribution Mapping for Autonomous Mobile Robots**. *Enviado y actualmente bajo revisión* (2020).

Capítulos de Libros

- *Andres Gongora, David Chaves, Alberto Jaenal, Javier Monroy y Javier Gonzalez-Jimenez.* **Toward the Generation of Smell Maps: Matching Electro-Chemical Sensor Information with Human Odor Perception.** Frontiers in Artificial Intelligence and Applications (2018).

Congresos Científicos Internacionales

- *Andres Gongora, Javier Monroy y Javier Gonzalez-Jimenez.* **A Robotic Experiment Toward Understanding Human Gas-Source Localization Strategies.** International Symposium on Olfaction and Electronic Nose (ISOEN), Montreal, Canada (2017)
- *Andres Gongora, Javier Monroy y Javier Gonzalez-Jimenez.* **Gas Source Localization Strategies for Teleoperated Mobile Robots. An Experimental Analysis.** European Conference on Mobile Robots, Paris, Francia (2017).
- *Andres Gongora, Alberto Jaenal, David Chaves, Javier Monroy y Javier Gonzalez-Jimenez.* **Urban Monitoring of Unpleasant Odors with a Handheld Electronic Nose**. ISOCS/IEEE International Symposium on Olfaction and Electronic Nose (ISOEN), Fukuoka, Japón (2019).

Marco de la Tesis

Esta tesis es el resultado de 5 años de trabajo del autor como miembro del grupo de investigación de Machine Perception and Intelligent Robotics (MAPIR) del Departamento de Ingeniería de Sistemas y Automática de la Universidad de Málaga. Esta investigación ha sido financiada principalmente por el programa de becas FPI (Formación de Personal Investigador), apoyado por Junta de Andalucía, bajo el proyecto 2012-TEP-530, y por el Ministerio de Economía y Competitividad bajo el proyecto WISER (DPI2017-84827-R).

Durante este período, el autor completó el programa de doctorado en Ingeniería Mecatrónica en el Departamento de Ingeniería de Sistemas y Automática, donde obtuvo un sólido conocimiento en cuatro de los pilares fundamentales de la robótica: sistemas de control, sistemas electrónicos, sistemas mecánicos y computadores. Durante el programa, el doctorando también completó varios cursos técnicos como *Comunicación para Drones* por la Universidad de Málaga y asistió a seminarios variados como *Aerial Robotic Manipulators* y *Tutorial on Deep Learning with TensorFlow* los cuales, aunque ortogonales a la temática de la tesis, contribuyeron a obtener una perspectiva más amplia del estado del arte en la ingeniería actual. Así mismo, desde abril hasta julio de 2019, el autor realizó una estancia de investigación en el grupo Distributed Intelligent Systems and Algorithms Laboratory (DISAL) en la Escuela Politécnica de la Federación de Lausanne (EPFL), Suiza, bajo la supervisión del Prof. Dr. Alcherio Martinoli. Allí colaboró en un nuevo proyecto de búsqueda de fuentes de gas con robots mediante técnicas basadas en *infotaxis*, la obtención de información del entorno de forma eficiente, y adquirió información de primera mano de otros enfoques empleados para abordar la robótica olfativa, como por ejemplo la colaboración en enjambres de pequeños robots.

La beca FPI también ha ofrecido la oportunidad de colaborar como asistente de laboratorio con el Departamento de Ingeniería de Sistemas y Automática de la Universidad de Málaga. Durante el trabajo de esta Tesis Doctoral, el autor colaboró con la Escuela de Ingeniería Industrial en las asignaturas de *Ampliación de Robótica* (2016-2017), *Robótica y Automatización* (2016-2017), y *Regulación Automática* (2017-2018); y en la Escuela de Ingeniería Informática en las asignaturas de *Control por Computador* (2016-2017 y 2017-2018) y *Sistemas de Tiempo Real* (2016-2017). Durante este periodo, el autor también fue cotutor de los Trabajos Final de Grado (TFG) de Antonio Rodríguez Gómez-Guillamón, titulado *Desarrollo de una solución HW-SW de bajo coste para el seguimiento de personas controlado mediante una aplicación Android*, y de Louis Tomas Manzano Harmer, cuyo trabajo se titula *Desarollo de una solución HW-SW de bajo coste para la realización remota de prácticas de control automático*; al igual que cosupervisor de la Tesis de Máster en Ingeniería Mecatrónica de Javier Martínez Lahoz, titulada *Desarrollo integral y ensayos del escudo docente UMA-AEB-V2.0.0.*

Además de la investigación en el ámbito de esta Tesis Doctoral, el autor ha participado en otros proyectos del grupo MAPIR, algunos de ellos con temas relacionados:

Congresos Científicos Internacionales

- *Andres Gongora y Javier Gonzalez-Jimenez.* **Enhancement of a commercial multicopter for research in autonomous navigation**. 23rd Mediterranean Conference on Control and Automation (MED), Torremolinos, España (2015).

- *Andres Gongora, Juan-Antonio Fernández-Madrigal, Ana Cruz-Martín, Vicente Arevalo, Cipriano Galindo, Carlos Sanchez-Garrido, Javier Monroy y Francisco Fernandez-Canete.* **Shield Arduino de bajo coste para la enseñanza de asignaturas de Ingeniería**. II Jornadas de Computación Empotrada y Reconfigurable (JCER2017), Málaga, España (2017).

- *Javier Monroy, Francisco Melendez-Fernandez, Andres Gongora y Javier Gonzalez-Jimenez.* **Integrating Olfaction in a Robotic Telepresence Loop**. 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), Lisboa, Portugal (2017).

- *Ana Cruz-Martín, Andres Gongora, Juan-Antonio Fernández-Madrigal, Vicente Arevalo, Cipriano Galindo, Carlos Sanchez-Garrido, Javier Monroy y Francisco Fernandez-Canete.* **Innovación en el trabajo en**

laboratorio de una diversidad de asignaturas de ingeniería mediante el diseño y aplicación de una extensión de la plataforma de hardware abierto arduino. VI Jornadas de Innovación Educativa y Enseñanza Virtual (Universidad de Málaga), Malaga, España, (2018).

- *Andres Gongora, Juan-Antonio Fernández-Madrigal, Ana Cruz-Martín, Vicente Arévalo-Espejo, Cipriano Galindo-Andrades, Carlos Sánchez-Garrido, Javier Monroy, y Javier Fernández-Cañete.* **Optimizing Subject Design, Timing, and Focus in a Diversity of Engineering Courses Through the Use of a Low-Cost Arduino Shield**. 13th annual International Conference of Education, Research and Innovation (ICERI2020), Sevilla, España, (2020).

Patentes

- *Juan-Antonio Fernández-Madrigal, Andres Gongora, Ana Cruz-Martín, Vicente Arevalo, Cipriano Galindo, Javier Monroy y Carlos Sanchez-Garrido.* **ES2622734: Dispositivo electrónico educativo de funcionalidad múltiple para diversas ramas de la ingeniería**. (2018).

Estructura de la Tesis

Además de este resumen en castellano, el resto de la tesis está estructurada en los siguientes capítulos:

Capítulo 1: Introducción
resume los principales aspectos y contribuciones de la presente Tesis Doctoral.

Capítulo 2: Narices electrónicas
describe el diseño de una nariz electrónica para robótica e investigación, la cual será utilizada de forma directa o indirecta en los siguientes capítulos.

Capítulo 3: Búsqueda de fuentes de gas
ofrece una nueva perspectiva sobre la búsqueda de fuentes de olor con robots móviles, en la que se sustituye el comportamiento autónomo por teleoperación para estudiar la importancia de diferentes sensores y estrategias de búsqueda.

Capítulo 4: Estimación de mapas de distribución de gas
presenta un nuevo método para la generación de mapas de distribución de gas que, a base de incorporar información sobre el viento, logra extrapolar las medidas de forma fiable a espacios aún no visitados. También extiende dicho método para generar mapas de forma autónoma con un algoritmo que maximiza la información adquirida por el robot.

Capítulo 5: Reconocimiento de olores
busca asociar a la respuesta de los sensores de gas de la nariz electrónica aromas que puedan describirse con palabras simples, lo cual se emplea posteriormente para discriminar olores urbanos simples de sustancias nocivas en una pequeña localidad.

Capítulo 6: Conclusiones
ofrece algunas ideas finales sobre el trabajo realizado en esta Tesis Doctoral y presenta brevemente otras líneas de investigación aún abiertas sobre las contribuciones presentadas.

Conclusiones y Líneas de Trabajo Futuras

Como se ha discutido, la robótica olfativa tiene un gran potencial para todo tipo de aplicaciones. Al mejorar la capacidad sensorial de los robots, estos obtienen un nuevo abanico de información sobre el entorno en el que trabajan y, por tanto, una mejor capacidad para tomar decisiones autónomas. Sin embargo, y al igual que con cualquier tecnología nueva, la robótica olfativa viene acompañada por una serie de retos a superar. Así, en la presente tesis hemos afrontado cuatro de las principales limitaciones del estado del arte actual.

En primer lugar, hemos abordado las narices electrónicas y sus limitaciones para la robótica móvil, especialmente en cuanto a versatilidad (gases que pueden detectar, facilidad de uso, etc.) y portabilidad (dimensiones, consumo, etc.). A continuación, nos hemos centrado en dos de las aplicaciones principales de la robótica olfativa, a saber, la búsqueda de fuente de olores y la estimación de la distribución espacial de gases. En cuanto a la primera, hemos cambiado de la perspectiva de la literatura actual, la de robots totalmente autónomos, a la de robots teleoperados; con lo que hemos obtenido una mejor comprensión sobre los requisitos sensoriales de los mismos y sobre cómo buscan los humanos en estas situaciones. En cuanto al mapeado de gases, hemos desarrollado un nuevo algoritmo que combina información de gas, viento y obstáculos para generar mapas completos del entorno sin necesidad de medir en cada posición. Y, por último, hemos contribuido al reconocimiento automático de olores con narices electrónicas, lo cual permite a los robots obtener información semántica sobre los gases que detectan. En general, las conclusiones principales de esta tesis en cuanto a cada bloque son:

- **Narices electrónicas**. Las narices electrónicas modulares son una alternativa viable al estado del arte actual. Aunque nuestro diseño conlleva redundancia de componentes electrónicos al duplicarlos en varias placas, las ventajas superan a los inconvenientes: nuestra nariz electrónica es totalmente configurable y reutilizable y es posible añadir nuevos sensores en el futuro sin necesidad de cambiar el diseño completo.

- **Búsqueda de fuentes de olores**. Observamos que durante la búsqueda de fuentes de olores teleoperada, los operarios utilizan una técnica muy similar a lo que se conoce como infotaxis. En lugar de seguir al aroma detectado directamente hasta su origen, nuestros sujetos de prueba realizaron una exploración del entorno que les permitiese descartar todas las opciones incorrectas hasta quedarse solo con la más probable. Curiosamente, este comportamiento resultó ser exitoso incluso cuando el robot no disponía de información semántica del entorno (por ejemplo, la posición de posibles alternativas) y solamente estaba equipado con una nariz electrónica, lo cual convierte a infotaxis en un excelente candidato para robots autónomos.

- **Estimación de la distribución espacial de gases**. En esta tesis hemos presentado *GW-GMRF*, una nueva técnica probabilística para la generación de mapas de gas que también modela corrientes de viento. Hemos demostrado experimentalmente que nuestro método requiere de mayor computación que otras técnicas similares para tiempo real pero que, a cambio, la fiabilidad de los mapas generados es considerablemente mayor, lo que convierte a *GW-GMRF* en una excelente herramienta para aplicaciones en las que el robot ha de tomar decisiones rápidas con una exploración mínima del entorno. En este sentido, GW-GMRF también puede operar de forma completamente autónoma mediante nuestro algoritmo IGDM, lo cual le permite optimizar el trayecto recorrido por el robot y, así, reducir el tiempo requerido para la exploración aún más.
- **Reconocimiento automático de olores**. Hemos entrenado al clasificador de una nariz electrónica para el reconocimiento de olores y gases conforme a la percepción humana, lo que podría proporcionar a un robot autónomo información semántica adicional. En nuestros experimentos, nuestra nariz electrónica fue capaz de reconocer la calidad subjetiva del aire en entornos urbanos y, combinado con un GPS, trazar el contorno de un vertido tóxico. Como contribución paralela, también hemos publicado la base de datos etiquetada manualmente con la que hemos entrenado al clasificador.

Líneas de Trabajo Futuras

Como suele ocurrir en cualquier proyecto, nuestro trabajo nos ha llevado a considerar otras líneas de investigación muy interesantes pero a las que no ha dado tiempo. A continuación, describimos algunas de las que queremos abordar en el futuro próximo.

Mapeado y búsqueda de olores subjetivos. El próximo objetivo de nuestro trabajo es la combinación de reconocimiento automático de olores (Chapter 5) con la búsqueda de sus orígenes (Chapter 3) y estimación de sus campos de concentración (Chapter 4). La implementación de esta técnica es, en principio, relativamente sencilla, ya que únicamente habría que sustituir la concentración de gas medida por la intensidad subjetiva del olor detectado. Sin embargo, el problema se vuelve muy interesante si se aplica a varios olores simultáneamente, como, por ejemplo, para utilizar la información que ha recopilado el robot mientras buscaba un primer olor para acelerar la posterior búsqueda de un segundo olor.

Mapas de gas de resolución variable. El método para estimar la distribución de gases presentado en esta tesis emplea una resolución constante para el mapa. Esto significa que todas las áreas del entorno requieren de la misma cantidad de computación, independientemente de si tienen gas o no, lo cual impone un límite máximo a la resolución en la práctica, ya que hay que calcular todas las celdas aunque no sean de interés. Una mejor alternativa sería un mapa con resolución variable, tal que las áreas sin gas pudiesen agruparse para acelerar la computación, a la vez que poder captar con mayor detalle aquellas en las que sí hay. No obstante, adaptar nuestro método para resolución variable no parece trivial a primeras, ya que cada celda del campo de Markov subyacente tendría un número variable de conexiones que impediría la formulación eficiente que proponemos en el Capítulo 4.

Algoritmo bioinspirado para la búsqueda de fuente de olores. Hemos recopilado un importante conjunto de datos al investigar la búsqueda de fuente de olores en el contexto de la teleoperación. Un uso interesante para estos datos podría ser el desarrollo de una nueva técnica bioinspirada, por ejemplo, mediante aprendizaje por ordenador para emular el comportamiento de búsqueda humano. Como alternativa, se podría optar por un enfoque heurístico y desarrollar el algoritmo atendiendo a que el comportamiento observado se parece a infotaxis, como se describe en el Capítulo 3.

Punto y aparte

Esta sección concluye el resumen de la presente tesis, *Enhancement of the Sensory Capabilities of Mobile Robots through Artificial Olfaction*. El lector puede continuar con los siguientes capítulos, en el idioma inglés, donde se describen con mayor detalle las contribuciones de la misma.

1 Introduction

Today is Saturday, but not just any Saturday. Today is Saturday 23'th September 2124, a very special day and not only because it is the autumn equinox.

Just a few months ago you finished your PhD. and moved to Big City in search of new opportunities. Here you live just like anybody else, in one of the countless, advertisement-wrapped, sky-scrapers that make up for most of the real-state. Your apartment is not precisely big, but it has everything you need and the rent is quite fair. When you moved in you were searching for your own path, but obviously, you are not living all by yourself. After all, you are not one of those crazy bio-radicals. You share your flat with your personal robot assistant, the very same you have had since you started university, although it is almost unrecognizable with all the upgrades you have installed after so many years. Compared to today's standard it is an outdated contraption that still relies on emulated intelligence, but it makes nonetheless good company aside from keeping everything clean and tidy the way you like it.

The reason why today is so special is that you have a date. In fact, it is your first date since you moved to the city, which does not precisely help with feeling nervous. Your date is not until much later, but you really prefer to wait a bit there than to be late and give a bad first impression. So you put on your favorite watch, the one your grandfather used to carry, and take your raincoat in case it starts raining again. But before you leave, you check yourself over one more time in the mirror and, just in case, also ask your robot how do you look. It approaches you with its usual familiarity, and while adjusting the neck of your shirt, comments on how much your date is going to like your new perfume.

Quite a bit less nervous, you open the door to the corridor when your robot, still by your side, suggests that you take your active breathing mask. It has detected elevated O_3 levels in the air that just entered through the door. Pollution seems to be especially bad today, although you did not notice it thanks to your indoor air-processing unit. Your robotic butler also informs you about the safest route in case you would like to walk on the surface instead of taking the underground; the city's sensor network provides a real-time map of air composition to all its inhabitants just for this purpose. Everyone has had to adjust to the new conditions, the world is teetering on the edge of environmental oblivion. But today is not the day to worry about such things. Today, you have a date.

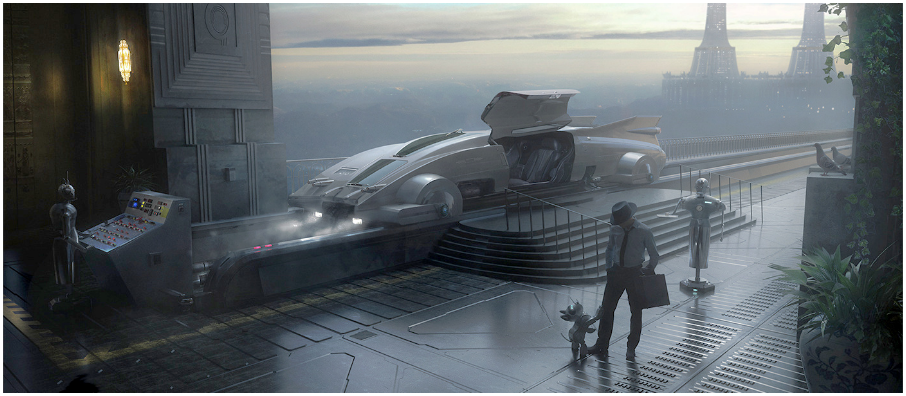

Figure 1.1: One day, robots might be omnipresent in our daily lives. They will look, react and behave just like any other intelligent being: fully aware of their surroundings and able to adapt to external changes. Illustration from the online novel *Aurora Noir*.

Perhaps this story contains more fiction than science, but so far, the future has always surpassed all our expectations. If we come back to the present and talk about autonomous mobile-robotics in current terms, we are referring to the technology that allows a mechanical agent to interact with its surroundings in an intelligent and self-sufficient way. Featured examples of the progress made in this field include the exploration of human-unreachable locations, like the case of Mars rovers or underwater bots used for marine research, or the less prominent but equally important assistance-robots, designed to extend the independence of elderly people living alone at home. But regardless of the application, all mobile robots have one thing in common: the need to gather information about the surrounding environment to make intelligent decisions. In this context, it is not uncommon to look at living beings for inspiration, where we observe that whether it is to look for food, detect predators, or to communicate, we have developed a wide range of varied senses. Among them, although maybe not so widespread in robotics, is the sense of smell.

By providing a robot with the ability to perceive the composition of the air, i.e. artificial olfaction, it gains access to a whole new dimension of information that might otherwise not be available. For example, in the cases mentioned above, a martian *rover* could detect the presence of organic gases (e.g. methane) accumulated in the subsoil, or a robot for elderly assistance could check if the food in the refrigerator is still good. Other possible applications of olfactory robotics include the automatic detection of gas leaks in industrial facilities, and speeding up the search for survivors in collapsed buildings by detecting the CO_2 exhaled by trapped people. And yet another example are aerial robots for ambient pollution monitoring, which can measure smog at different heights and between buildings to aid in deciding the most efficient actions to combat it. All in all, there are as many uses for olfactory robotics as applications where a robot might benefit from sensing airborne chemicals, regardless of whether it is for scientific, safety, biomedical, military, or any other such application.

Admittedly, this technology is still not as advanced as other aspects of mobile robotics. Integrating artificial olfaction into a robot and then designing new strategies that exploit this new information in an efficient way is no easy feat. But with all the advantages it offers, it is not unthinkable that olfaction will be someday just another aspect of any common robot.

1.1 Motivation

Despite the plethora of benefits that artificial olfaction offers to mobile robots [1], there are still several key elements that need to be addressed before it becomes a readily available technology. To begin with, one of its major limitations lies in the very devices responsible for acquiring olfactory information, usually referred to as electronic noses (e-noses). Most e-noses are formed by a matrix of electrochemical sensors, which can individually measure a wide range of volatiles (CO_2, CO, CH_4, etc.) but do not provide information about the chemical identity or composition of the analyte [2]. Therefore, the joint response of these sensors is treated as an "olfactory fingerprint" that, through machine learning, allows e-noses to identify [3, 4] and/or quantify [5, 6] certain gases. As such, this is not a new concept as evidenced by the availability of various commercial solutions[1]. Depending on their intended use, these are usually bulky, heavy and expensive devices that have been designed for precision (i.e. laboratory equipment), or on the

[1] Today we carry all sorts of sensors on us, conveniently embedded into our smartphones and watches, and our homes and cities are covered with even more of them to make our lives that much *smarter*. But even though the first modern e-nose was presented in 1982 [3], e-noses remain a niche technology that is usually limited to academia and specialized industrial applications; as evidenced by the fact that most laymen have never heard of them and that they are hard to come by. In this sense, there are many advanced e-nose solutions for specific use-cases, but overall, this is still a relative new technology that is just starting to take off.

contrary, they are very compact and lightweight (i.e. hand-held) but limited to specific gases [7, 8]. Yet, hardly any of these e-noses are suited for olfactory robotics, which requires portable and lightweight solutions (most robots have strict weight and power limitations) that are simultaneously sensitive to a wide range of generic volatiles (similar to our mammal noses). This is consequently a great design challenge for the current state of the art [49], but without such a device, olfactory robotics will always remain restrained in terms of its practical possibilities.

Another shortcoming of olfactory robotics is related to the intrinsic difficulty of sensing gases. Conventional e-noses, like just described, rely on physical contact with the analyte to measure it and are thus limited to point samples (i.e. they cannot measure from a distance). As a consequence, any robot equipped with these e-noses can only sample at its current location and, even with pumps or fans to aspire the air [9], a small space around it. This can be an inconvenience if the robot wants to detect the presence of gas (e.g. to trigger an alarm), but becomes a critical limitation if it also needs knowledge about the gradient and/or contour of the distribution; the robot can not instantaneously perceive how the gases are spread in the work environment, yet sampling every single location is either very time consuming or, more often than not, completely intractable[2]. The only solution is to devise an efficient sensing-strategy that adapts to the robot's sensors and intended use, yet retains an acceptable compromise between accuracy and performance. Such is the case for the two major applications in olfactory robotics [13], namely gas source localization (GSL) and gas distribution mapping (GDM).

- **GSL** employs autonomous robots to search for the release point of volatile substances [14, 15] like, for example, gas leaks in inaccessible areas. This has all sorts of potential applications, especially in the context of industrial safety [16, 17, 18, 19, 20] and is thus a highly researched topic [21]. But despite all efforts, there is still no satisfactory solution that works in generic and uncontrolled environments [13, 22, 23]. So far, the chaotic nature of gases [24] has meant that GSL is only suited for relative simplistic conditions (i.e. unidirectional and laminar wind fields [14, 25], absence of obstacles [26, 27], overspecialization to a single environment [28], etc.) that are far from the complexity of real-world

[2]This limitation also holds for tunable laser absorption spectroscopy sensors [10], an alternative to conventional e-noses that measures gas with a laser-beam. Although tunable laser absorption spectroscopy does work at a distance and offers several advantages over gas-sensor that rely on physical contact (in the previous example, it is substantially easier for a robot to detect the gas to trigger an alarm), it is still not able to immediately perceive the spatial distribution of volatiles. Because of its working principle, the value reported by the laser is always the integrated gas concentration along the whole beam. Meaning that the laser can not measure individual values along its length, and that in turn, any position of interest must thus be observed from all possible angles to factor out the surrounding gas from its measurement [11, 12].

settings. Although GSL is conceptually simple, the need for an efficient search strategy remains. All we know for sure is that it should be, in principle, doable with a point sensor like an electronic nose, since most animals can trace a smell even under adverse conditions.

- **GDM** is meant to provide a map of the spatial distribution of gases for applications like air quality control [29, 30]. Here, the robots need to extrapolate the gas intensity at unvisited locations, but because their resources are usually limited, they may not incur into computationally expensive computational fluid dynamics (CFD) simulations to obtain exact results. The current state of the art of GDM is therefore only meant for open spaces with no or little obstacles [31, 32] or applications where a local estimate suffices [33], or it does not consider air currents [34] to predict, for instance, additional gas in the downwind direction. There is still room for improvement, and thus, for alternative GDM solutions that address these issues.

Finally, we must also remark on the robots' ability to interpret and draw meaning from the volatiles they detect. Inherently, this topic is more closely related to e-noses that to robotics, since it only depends on the post-processing of the gas sensors and the employed machine-learning techniques. But without it, olfactory robotics can not address tasks where the robots need to identify a smell or where they need to convey it to a human in simple and intuitive terms. For instance, there are many applications where an e-nose is trained to recognize all sorts of wines [35] or olive oils [36], but do so according to abstract descriptors that have no direct equivalence with notions such as acidity or sweetness. In contrast, the ideal solution would be if robots could perceive the odors akin to how we do, but with the added advantage of also sensing odorless substances like CO_2 or water vapor, that is, if robots could actually *smell* the gases they sense with their e-noses. Allowing them to tell if someone is wearing too much perfume yet, just like in the introduction of this thesis, take appropriate safety measures if they detect noxious chemicals in the air.

1.2 Contributions

This thesis takes a broad approach to olfactory robotics to address some of the above-described limitations. In the first place, we contribute to the field of e-noses with a design specifically meant for mobile robots, but that can also be operated manually to facilitate experimentation. With it, we then take an alternative approach to GSL, where we introduce the human reasoning-capabilities into the search process by means of a teleoperated robot. This offers an effective alternative for situations in which an autonomous robot might be overwhelmed, and at the same time, serves to study how the operators remain efficient under those circumstances. Then, we test the e-nose with a novel GDM model that allows autonomous mobile-robots to estimate surrounding gas-distributions with fewer observations than previous approaches. Our method accomplishes this by jointly exploiting the wind and obstacle information available at each instant of time, which is particularly suited for complex indoor environments. Moreover, we have extended this method with the insight we have gained from the aforementioned teleoperation approach, arriving at a fully autonomous solution for automatic gas mapping; a robot using our algorithm can create a detailed gas map of its surrounding, choosing and traveling to the optimal sample locations without need for human intervention. Lastly, we also present a small contribution to the topic of "smelling with robots", where we match the e-nose's response to the human perception for the automatic recognition of common urban-smells and chemicals of interest. Hereby, the contributions of this thesis can be split into the following four main topics.

1.2.1 Contribution to Electronic Noses

Our first work [8] seeks the development of an electronic nose that meets the requirements of mobile robotics, especially concerning the relation between portability (i.e. weight, consumption, and dimensions) and the range of volatiles it can detect (i.e. the number of sensors it carries). Ideally, such an electronic nose should simultaneously excel at both requirements to allow a robot to adapt to a wide range of olfaction related applications without encumbering it. But, given the current capabilities of gas transducers and their sizes [37], it must often favor one over the other. Although there is a wide variety of gas-sensor technologies to choose from, each with its advantages and disadvantages in terms of detectable gases, sensitivity, and tolerance to environmental factors (e.g. humidity, temperature) [2], none excels in all categories. Which becomes an additional burden if one also considers that most applications involve completely different gases and concentration ranges, and that no single sensor combination can address them all. Hence, most e-nose designs are forced to choose between a high number of sensors to offer an informative output or prioritize portability over versatility.

To address this challenge, at least until a better transducer technology becomes available, we propose a modular electronic nose architecture based on a *building-block* philosophy. Instead of relying on a single design with fixed sensors, our e-noses can be quickly reconfigured to carry the sensors modules it needs for a specific application, as well as to remove those no longer needed or to connect ancillary devices such as Bluetooth or GPS. This does naturally not solve the root problem, but it offers a convenient solution that drastically reduces the effort required to develop a new e-nose for a robot. It eases experimentation with different sensor combinations and allows for a higher degree of reusability if the requirements change.

1.2.2 Contributions to Gas Source Localization

Given that the accuracy of autonomous GSL is still low in complex and uncontrolled environments despite a significant amount of research on the topic [13], we have chosen to take a step back and analyze the problem from a different perspective. Instead of relying on autonomous robots, we address the issue through teleoperation; so that we retain the robot's ability to measure gas at remote locations, but replace its *intelligence* by a human operator [38] to deal with complex situations. Naturally, this compromise sacrifices some of the advantages offered by a completely autonomous robot, but it allows for applications that are still not feasible with current solutions and, more importantly, it offers a new venue to research the prerequisites for successful GSL.

We know that living beings, humans included, have the required skills to find the origin of smells under the right conditions. Intuitively, the combination of olfactory information with other sensory inputs (e.g. vision, perceived wind flow, etc.) is key for our success. But probably more important than the perception itself is how we use this information to guide our search. Hereof, our goal by relying on teleoperation is to obtain a better insight into the human GSL behavior when the available information is limited to the robot's perception. That is, to assess whether the sensors on a robot actually suffice to find a gas source, and if so, whether the operators came up with a specific search strategy do so.

We contribute to this end with three research publications [39, 42, 43] where we approach teleoperated GSL through simulation as well as with real experiments. These works show not only that GSL is indeed possible even under minimal sensor configurations, but that the way we humans search is very akin to what is known in the literature as *infotaxis* [44]: an information-driven search strategy with a strong probabilistic component. In addition, we also contribute through these works with two big datasets (one in a simulated environment, and the other in a real one) that could be used, among others, to devise new bio-inspired search techniques.

1.2.3 Contribution to Gas Distribution Mapping

With this contribution we address the problem of GDM in which the robot has to estimate the gas concentration at locations that were not subject to direct sampling. We have devised to this end a mathematical model of how the gas distributes among adjacent positions depending on wind currents and obstacles in the environment, and the most likely value one would get with an electronic nose. Accordingly, by using this model "in reverse" with a maximum a posteriori estimation, the robot can compute the distribution that best explains its observations while it explores.

The main advantage of our approach [45] over similar techniques is that we also model the wind in the environment to reduce the number of observations the robot has to gather. For example, if there is a very long corridor with a single entrance and a single exit, then measuring at one end should provide some information about what is to be expected on the opposing end. After all, if gas and wind come in from one side, they must necessarily exit from the other. Moreover, because our GDM formulation combines all samples under a probabilistic approach, it can assign different uncertainties to different locations of the output map. This allows it to deal with more challenging situations, such as physically isolated areas, turbulences near obstacles, or environments that are only partially explored, without impairing its overall reliability.

Furthermore, we extended our method with a new algorithm that enables a fully autonomous robot to map an unknown gas distribution by exploring along an optimal path [46]. We know from our previous teleoperation experiments that gaining information, in itself, may play a role of similar importance to that of the gas distribution it reveals. Consequently, we have centered our efforts on closing the GDM control loop with a focus on the aforementioned *infotaxis*. We have developed an iterative algorithm that leverages the robot's latest gas map to send it, among all reachable locations, to the one that provides the most information when sampled. By also factoring in energy expenditure and exploration time, while maintaining a reasonable balance between mapping new areas and improving the map's reliability for those already sampled, we arrive at an optimal solution. A process that can be summarized as information-driven gas distribution mapping, and lets a robot adjust its exploration in real-time as new data becomes available.

1.2.4 Contribution to Automatic Smell Recognition

In this last group of contributions, published in [47, 48], we address the problem of smell recognition through artificial olfaction. Our goal is to match the output of the sensors on an electronic nose to the human perception, such that detected aromas can be identified through a simple yet descriptive label (e.g. flower, tobacco, perfume) that the robot can later use for other tasks. The main difficulty herein is the complexity of the gas-sensors' output to even the simplest of volatiles, which prevents a direct matching to the corresponding aromas. Our solution consists therefore in gathering a training dataset of the raw output of a wearable configuration of our electronic nose (from Section 1.2.2) to common urban smells, and then train with it several machine learning algorithms.

Although this section of the thesis involves no robots, it still serves as a proof of concept for adding semantic meaning to e-nose readings. The result of our first work [47] was the automatic generation of city-scaled odor-maps by walking around with the e-nose, and for our second work [48] we added samples of toxic gases to also map the impact of an environmental accident. Meaning that this same information could be available to robots during operation, and thus aid in their decision-making processes.

1.3 Publications

The present thesis encompasses the following publications:

1.3.1 Journals

- *Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez.* **An Electronic Architecture for Multi-Purpose Artificial Noses.** Journal of Sensors (2018).
- *Andres Gongora and Javier Gonzalez-Jimenez.* **Olfactory Telerobotics. A Feasible Solution for Teleoperated Localization of Gas Sources?** Robotics and Autonomous Systems (2019).
- *Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez.* **Joint Estimation of Gas & Wind Maps for Fast-Response Applications**. Applied Mathematical Modelling (2020).
- *Andres Gongora, Faezeh Rahbar, Chiara Ercolani, Javier Monroy, Javier Gonzalez-Jimenez, and Alcherio Martinoli.* **Information-Driven Gas Distribution Mapping for Autonomous Mobile Robots**. *Submitted and under review* (2020).

1.3.2 Book chapters

- *Andres Gongora, David Chaves, Alberto Jaenal, Javier Monroy, and Javier Gonzalez-Jimenez.* **Toward the Generation of Smell Maps: Matching Electro-Chemical Sensor Information with Human Odor Perception.** Frontiers in Artificial Intelligence and Applications (2018).

1.3.3 International Conferences

- *Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez.* **A Robotic Experiment Toward Understanding Human Gas-Source Localization Strategies.** International Symposium on Olfaction and Electronic Nose (ISOEN), Montreal, Canada (2017)

- *Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez.* **Gas Source Localization Strategies for Teleoperated Mobile Robots. An Experimental Analysis.** European Conference on Mobile Robots, Paris, France (2017).
- *Andres Gongora, Alberto Jaenal, David Chaves, Javier Monroy, and Javier Gonzalez-Jimenez.* **Urban Monitoring of Unpleasant Odors with a Handheld Electronic Nose**. ISOCS/IEEE International Symposium on Olfaction and Electronic Nose (ISOEN), Fukuoka, Japan (2019).

1.4 Framework and Timeline

This doctoral thesis is the result of 5 years of work by the author as a member of the *Machine Perception and Intelligent Robotics* (MAPIR) research group[3], part of the Department of System Engineering and Automation of the University of Malaga. Here, the author started to work under the supervision of Prof. Javier González Jiménez during the B.Sc. dissertation *Enhancement of a commercial multicopter for research in autonomous navigation*, and later, the Master Thesis *Development of a lightweight and compact multi-sensor system for air-composition analysis.* After this, the author received an FPI grant (*Formación de Personal Investigador*) by the Governments of Spain and Andalusia, and the European Regional Development Fund under the research project TEP530, which funded most of this research.

During this period, the author completed the doctoral program in *Mechatronics Engineering* in the Department of System Engineering and Automation, where he obtained a solid background in the four fundamental areas of robotics: control systems, electronic systems, mechanical systems, and computers. During the doctoral program, the author also completed several technical courses such as *Communications for drones* at the University of Malaga, and assisted to talks like *Aerial Robotic Manipulators* and *Tutorial on Deep Learning with TensorFlow*, which despite diverging from the main theme of this thesis provided a broad overview of the current state of the art of major engineering topics.

The author also stayed from April to July 2019 with the *Distributed Intelligent Systems and Algorithms Laboratory*[4] (DISAL) at the Swiss Federal Institute of Technology in Lausanne (EPFL), Switzerland, under the supervision of Prof. Dr. Alcherio Martinoli. There he collaborated in a novel approach to gas source localization based on *infotaxis*, an efficient

[3] http://mapir.uma.es
[4] https://www.epfl.ch/labs/disal/

search strategy based on obtaining information from the environment, and learned first-hand about alternative approaches to olfactory robotics like the synergistic cooperation of swarms of small mobile robots.

The aforementioned FPI grant also offered the opportunity to collaborate as a laboratory assistant and lecturer at the Department of System Engineering and Automation. During this thesis work, the author taught *Advanced Robotics* (2016-2017), Robotics and Automation (2016-2017), and *Control Theory* (2017-2018) at the Engineering School, at the University of Malaga; and *Computer Control* (2016-2017 and 2017-2018) and *Real Time Systems* (2016-2017) at the Computer Science Faculty, also at the University of Malaga. Moreover, the author also was co-director of the B.Sc. dissertations of Antonio Rodríguez Gómez-Guillamón, entitled *Development of a Low-cost Solution for People Tracking*, and Louis Tomas Manzano Harmer, entitled *An HW-SW Solution for an Online Control-theory Training Laboratory*; as well as co-supervisor of the Master Thesis of Javier Martinez Lahoz, entitled *Design, Development, and Testing of the Arduino Training Shield UMA-AEB-V2.0.0.*

In addition to the research in the scope of this thesis, the author has been also involved in other, aprallel research topics that ahve led to the following publications:

1.4.1 International Conferences

- *Andres Gongora y Javier Gonzalez-Jimenez.* **Enhancement of a commercial multicopter for research in autonomous navigation**. 23rd Mediterranean Conference on Control and Automation (MED), Torremolinos, Spain (2015).

- *Andres Gongora, Juan-Antonio Fernández-Madrigal, Ana Cruz-Martín, Vicente Arevalo, Cipriano Galindo, Carlos Sanchez-Garrido, Javier Monroy y Francisco Fernandez-Canete.* **Shield Arduino de bajo coste para la enseñanza de asignaturas de Ingeniería**. II Jornadas de Computación Empotrada y Reconfigurable (JCER2017), Malaga, Spain (2017).

- *Javier Monroy, Francisco Melendez-Fernandez, Andres Gongora y Javier Gonzalez-Jimenez.* **Integrating Olfaction in a Robotic Telepresence Loop**. 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), Lisboa, Portugal (2017).

- *Ana Cruz-Martín, Andres Gongora, Juan-Antonio Fernández-Madrigal, Vicente Arevalo, Cipriano Galindo, Carlos Sanchez-Garrido, Javier Monroy y Francisco Fernandez-Canete.* **Innovación en el trabajo en laboratorio de una diversidad de asignaturas de ingeniería mediante el diseño y aplicación de una extensión de la plataforma de hardware abierto arduino**. VI Jornadas de Innovación Educativa y Enseñanza Virtual (Universidad de Málaga), Malaga, Spain, (2018).

- *Andres Gongora, Juan-Antonio Fernández-Madrigal, Ana Cruz-Martín, Vicente Arévalo-Espejo, Cipriano Galindo-Andrades, Carlos Sánchez-Garrido, Javier Monroy, and Javier Fernández-Cañete.* **Optimizing Subject Design, Timing, and Focus in a Diversity of Engineering Courses Through the Use of a Low-Cost Arduino Shield**. 13th annual International Conference of Education, Research and Innovation (ICERI2020), Seville, Spain, (2020).

1.4.2 Patents

- *Juan-Antonio Fernández-Madrigal, Andres Gongora, Ana Cruz-Martín, Vicente Arevalo, Cipriano Galindo, Javier Monroy y Carlos Sanchez-Garrido.* **ES2622734: Dispositivo electrónico educativo de funcionalidad múltiple para diversas ramas de la ingeniería**. (2018).

1.5 Outline

The rest of this thesis encompasses our contributions to the field of olfactory robotics, organized into the following chapters:

Chapter 2: Design of an electronic nose for robotics
describes a modular e-nose architecture for research and presents a working prototype that is employed throughout this thesis.

Chapter 3: Gas Source Localization
resorts to teleoperation to understand the importance of various sensors for successful GSL in complex environments, and provides an insight into the human search-behavior for the future development of fully autonomous solutions.

Chapter 4: Gas Distribution Mapping
proposes a new method that exploits wind-information to provide more accurate estimates at unvisited locations with fewer data-samples than

similar techniques, as well as an algorithm for autonomous gas mapping that maximizes the robot's information gain.

Chapter 5: Smell Recognition
describes how raw e-nose-readings can be matched to intuitive yet semantic meaningful labels for smells and chemical compounds, which are later used to automatically map the pleasantness of urban air (as perceived by humans) in one case scenario, and delimit the reach of a toxic spill in another.

Chapter 6: Conclusions and Final Thoughts
provides some final insights drawn from the work done in this thesis and briefly introduces the future lines still open to research in relation to the contributions of this work.

2 Electronic Nose

This chapter describes the development of an electronic nose (e-nose) for mobile robots. Because the range of possible applications is quite diverse yet we would like to address them all, our design is based on a modular architecture that can adapt to different requirements. The result of this work is key for the remainder of the Thesis, as e-noses are the cornerstone of gas source localization, gas distribution mapping, and smell recognition.

2.1 Introduction

The most straightforward approach to acquire chemometric data is an electronic nose. This device consists of an array of small non-selective gas sensors that respond indistinguishably to various chemicals, but whose combined output can be processed with a classification algorithm to recognize and measure specific volatile substances [4, 47]. The main advantage of electronic noses is that they are cheap and compact, especially when compared to technologies like chromatography-mass spectrometry [50] or tunable laser-diode spectroscopy [12]. This comes however at the cost of diminished sensing capabilities, which limits the range and complexity of detectable gases [7].

In the early years of this technology, at the end of the 20th century, limitations in electronic nose performance was partly due to the available machine learning techniques and computation resources [2]. After all, the defining property of an electronic nose is its ability to *recognize* volatiles, which is the result of processing the sensor output with a classification algorithm. But with recent advances in the field and the boost brought by *Deep Learning* [51, 52, 53, 54], electronic noses are now mostly constrained by their sensors.

Common gas sensor technologies include metal oxide (MOX), amperometric electrochemical (AEC), quartz crystal microbalance (QCM), conducting polymers (CP), and surface acoustic wave (SAW) among others [55, 56, 57, 58, 59]. Their underlying working principle is very different, but they all exploit some chemical or mechanical properties of gases to convert their concentration into an electric signal. Hence, by manufacturing them with slight variations (i.e. different coatings, resonant frequencies, etc.) they become reactive to different substances, which can then be exploited to obtain a *fingerprint* of an aroma if several of these sensors are combined [2]. Notwithstanding, the concentration-range and type of gases that can be detected with any single technology is limited, hence, their combination is preferred to attain a more informative response to the analyte [7].

Furthermore, any particular sensor combinations can only identify a limited set of aromas. An electronic nose with more sensors usually provides a better *fingerprint* and, in turn, can differentiate between more substances. However, this does not scale well, as it would not be feasible to carry all possible sensors on a single device yet retain the above-mentioned advantages of cost and portability. Thus, it also becomes appealing to allow an electronic nose to be reconfigured with interchangeable sensors to adapt to the application at hand.

These two requisites combined, heterogeneity and reconfigurability, are particularly important for research in olfactory robotics. The possibility to change the technology of the sensors is useful to adapt to different gases and concentrations for the experiments. But more importantly, it also allows for a multipurpose and reusable electronic nose with only the most essential sensors to save on weight and power consumption, and thus eliminating the need for a separate design for each application. For example, the same electronic nose could be used on a lightweight drone, with only one or two sensors when the target gas is easy to detect, or on a wheeled ground robot that may carry more weight, with an assorted sensor array to detect complex aromas. But in spite the advantages of both these characteristics, there is no commercial electronic nose that offers them both.

2.2 Contribution

The main difficulty of building an electronic nose that combines heterogeneous technologies with a reconfigurable design comes from the electronic requirements of the different gas-sensors. For instance, MOX sensors operate in a voltage divider configuration and need quite some power for their heating elements, whereas AEC sensors require a precise and low-noise reference current that is usually in the range of μA. If the device were to use a single sensor-technology, it could simply offer an array of sockets to plug in the individual transducers. Or if a compromise were possible, it may instead use several banks of sockets, each for a different technology. However, a completely configurable electronic nose should not be limited, at least by design, in the number of technology of sensors it can carry.

In our work, presented in [8], we addressed this issue with a design built around the idea of nodes, intelligent and self-contained electronic boards that operate without the need for a central arbiter. Each node host one or more sensors and manages all its onboard resources, such that all implementation details remain hidden behind a shared power and communications interface. In this way the nodes behave like basic building blocks for the electronic nose, allowing for a quick reconfiguration and reuse of all its components, as well as easing the future integration of new technologies which might not yet be available on the market. Another important advantage of this design is that it also allows for the integration of ancillary devices, such as GPS to obtain geo-referenced measurements or Bluetooth for wireless communications.

To test our architecture we built eight different electronic nose nodes and, in the case of those intended for gas sensing, populated them with different MOX, AEC, and SMD-MOX sensors. This allowed us to build, as described in our manuscript (Section 2.A), three different electronic nose implementation for completely different purposes. We created a portable version protected by a 3D-printed enclosure for olfactory robotics and used it during our experiments in Chapters 3 and 4. We also built a wearable version powered by a built-in battery for smell-recognition research in Chapter 5, which we later reused for the detection of toxic gases. Lastly, and even though we did not get to apply in practice, we also built multiple sensor clusters as a proof of concept for distributed sensor networks.

The development of the presented electronic nose architecture and its subsequent implementation has taken up a major part of this thesis. But all in all, it has greatly facilitated the rest of our work, and we believe that it is of great interest to other researchers who may seek to develop their own custom gas-sensing solutions.

2.3 Implementation Remarks

We would like to seize this opportunity to make some remarks on the implementation of our architecture. These mostly involve some simple specifications as well as recommendations for robustness. Any reader who might wish to replicate our design might benefit from them.

2.3.1 Effect of Force Airflow

We did not quantify the exact benefit of forced airflow over the sensors, but we quickly realized the need for it with our wearable electronic nose configuration. In our first experiments, we noticed that it was unable to detect smells of short duration, like when walking by a person with perfume. But more importantly, the sensors were recovering very slowly from continuous monitoring [60], which also limited the performance of the electronic nose for slower, ambient odors.

If need be, it is possible to offset the slow recovery of the sensors with a predictive model of their response curve [61]. However, if the power to do so is available, we highly encourage the use of a suction-fan and a solid enclosure to guide the air over the sensors. It makes the electronic nose more directional (it smells the air from one direction), but greatly improved its response time. Ideally, both these options can be combined to attain the best possible results.

2.3.2 Data bandwidth

With our design, communications between module are carried out by a modified MavLINK protocol [62] over I^2C in *fast mode*, with a baud-rate of 1 MHz, with multi-master broadcasts. For gas-reading messages, the header with meta-data is 20 bytes longs and the payload is a 4 byte-long float. This means that our implementation allows for roughly 4600 gas readings to be transmitted every second, and thus, for about 460 sensors on a single electronic nose at a 10 Hz refresh rate.

It is also possible to combine several readings in a single message to offset the weight of the message headers. For example, if a node were to host a multi-sensor matrix, like the one presented by Gardner et al. with 300 elements [63], the header would still be about 20 bytes long but the payload would grow to 1200 bytes. Using the same reasoning as above, the electronic nose has enough bandwidth for about 90 of such 300-sensor-chip readings every second.

2.3.3 Communications

A word on the multiple options to communicate with the electronic nose. In our architecture, each node *broadcasts* all its readings to the other nodes, such that any communication or storage node (i.e. USB, Bluetooth, SD-memory, etc.) may access said data. A nice side effect of this paradigm is that there might be more than one communication link to the electronic nose at a time. For example, the electronic nose can be connected over USB to the robot, and at the same time resend the same data over Bluetooth to an external computer for debugging purposes. This same behavior can also be exploited to create distributed sensor networks that behave as a single e-nose. Because each data packet jumps over Bluetooth, the electronic nose can be comprised of small node clusters, each equipped with wireless communications.

2.3.4 EMI performance

Special care must be taken when building an electronic nose like ours concerning electromagnetic interference (EMI). For our particular implementation, we chose two-layer printed circuit boards for cost-reduction. But in retrospect, we advise against it. By having only two layers to route on the small nodes all signals, power, and ground, the process became very tedious and time-consuming. But more importantly, it hindered good-practices [64, 65] such as solid ground-planes, short traces for high-frequency signals, clear separation between analog and digital circuitry, etc.

Although EMI performance is usually regarded in terms of noise emission, it is somewhat bidirectional and our nodes turned out to be more sensitive to noise-pickup than indented. This is no problem for most electronic nose configurations, like the ones used throughout this thesis. But we noticed that the e-nose readings became measurably noisier for test configurations that included the Bluetooth node. In these cases, the radio signal was coupling back into nearby electronics that, as in the case of the AEC sensors, might work with very small signals. Although this can be easily mitigated by mounting the Bluetooth node on the most external part (this also helps with range) and away from sensitive sensor nodes, we still consider it worth noting in case anyone wants to replicate our design.

2.A An Electronic Architecture for Multi-Purpose Artificial Noses

Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez

This paper deals with the design of an electronic device aimed at the detection and characterization of volatile chemical substances, that is, an electronic nose (e-nose). We pursue the development of a versatile, multi-purpose e-nose that can be employed for a wide variety of applications, integrates heterogeneous sensing technologies, and offers a mechanism to be customized for different requirements. To that end, we contribute with a fully-configurable and decentralized e-nose architecture based on self-contained and intelligent sensor-boards (i.e. modules). This design not only allows for the integration of heterogeneous gas-sensor technologies, like MOX and AEC sensors, but also of other components, such as GPS or Bluetooth, for a total of up to 127 individual modules. We describe an implementation of a fully operative prototype as illustrative example of its potential for sensor networks, mobile robotics, and wearable technologies, each using a different combinations of sensors.

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3 Gas Source Localization

In this chapter, we address gas source localization (GSL) from the perspective of teleoperation. Our goal is not the immediate development of a new search algorithm, but to understand how humans use the robot's sensor when tasked with finding a gas source. Our main contributions are two extensive datasets and an in-depth analysis of the gathered data, both of which provide new insight into the subject that might serve the future development of bio-inspired GSL techniques.

3.1 Introduction

Just like in the animal kingdom, one of the main uses for artificial olfaction in robotics is to search for the source of a smell. The exact end-goal may vary significantly from case to case, from watching for potential gas leaks in factories, to searching like a police dog for lost people or illegal substances. But regardless of the application, the robot has to (i) detect the target smell, (ii) follow it back to its origin, and once there, (iii) identify its exact source. There are accordingly three stages to gas source localization (GSL) [22], although the most relevant, as we shall see, is the second [21].

The first step during GSL, detecting the target volatile, refers to the situation where the robot is yet to find a trace of it before the actual search can start. Because the only role of artificial olfaction at this point is to determine whether the scent has been found, the process can be treated as a generic exploration problem. For instance, the robot could simply patrol along a fixed path to check for any gas or wait on standby until it is told where to go. Meaning that, although this first exploration is technically part of GSL, it is usually regarded as separate from the main problem [94].

Similarly, the third stage of GSL is also treated separately. Once the robot gets into the immediate proximity of the source, its exact identification is so conditioned by the intended application that it becomes a new problem altogether. For example, if a maintenance robot has followed a gas-leak to a pierced pipe, it must now rely on computer-vision to identify the exact position of the perforation to apply a sealant. Whereas, if a home-assistance robot found an unpleasant odor coming from the fridge, it is a semantic problem to determine what food items cause it and need to be thrown away.

The core of GSL is, therefore, the second stage, how the robot should follow the smell back to its origin. Although conceptually very simple, following a gas plume is a difficult challenge for a robot. The dynamic nature of gases [24] means that the plume may present discontinuities or local build-ups that are misleading, which is further aggravated by obstacles in the environment and chaotic wind currents. The result is often that the point of maximum concentration no longer matches the point of release, or on the contrary, that the gas field becomes relatively homogeneous and causes gradient-based searches to fail.

To overcome these difficulties, some GSL techniques have taken inspiration from the animal kingdom [95], such as SPIRAL [14], which mimics the search pattern of moths for situations where it is easy to lose track of the scent. Other techniques rely on probabilistic mathematics instead, like 3D Gaussian gas-plumes that the robot can compute without strictly following the concentration gradient [27] and that also works for swarm deployments [96]. Whereas yet others, including the surge-cast algorithm [97, 98], adapt their search to the complexity of the surrounding gas and wind distribution with state machines. But for the main part, most techniques could only be validated under laboratory conditions (e.g. laminar wind-flow, absence of obstacles, etc.) or are limited to specific environments (e.g. only outdoors, limited wind inlets/outlets, etc.). Despite all efforts, there is still no generic GSL solution that works in uncontrolled real-world settings and that adapts to unexpected changes, just like animals do.

3.2 Contribution

Given the many difficulties encountered by all other GSL methods, we do not seek the development of a new search technique. Instead, our goal is to take a step back and analyze the requirements of GSL from a different perspective. We have chosen to adapt GSL to teleoperation [38], as it is a mature technology that offers two advantages in this regard. The first is that it combines the ability to measure gas at remote or dangerous locations of robots with the human ability to make complex decisions. An alternative solution for applications that do not necessarily require autonomous systems. Whereas the second and most important advantage of teleoperated GSL is that we can assess with it if the sensors on an olfaction-enabled robot suffice to find a gas source, and whether the human operators use a specific search strategy to do so. In other words, by replacing the robot's *autonomous brain* with an operator, we can better study how the available sensor information can (or should) be used for GSL in complex environments.

We contribute to this end with three research publications. In the first of them [39], we performed a simulation experiment where volunteers had to find a gas source with a teleoperated robot while we recorder all state variables and user input for later analysis. By conducting the experiments under simulation, we mitigated external variations and ensured identical initial conditions for several realistic [40] gas and wind distributions. To assess the relevance of the sensors and have four difficulty levels, we incrementally added to the robot (i) an electronic nose, (ii) an anemometer, (iii) a predictive gas distribution map [41], and (iv) visual indicators on locations of interest. Regarding the latter, we would like to point out that the operators had at all times access to the robot's front camera for navigation purposes, but it was only during this sensor combination when we showed virtual pipes in the environment to visually highlight all possible gas release points. The result of this work was a dataset with over 150 experiments from 69 participants, which was then later analyzed in our second publication regarding GSL [42].

As was to be expected, the experiments in which the operator had access to all four sensory inputs performed the best. However, most of the other experiments were also successful, even when the robot was only equipped with the electronic nose, and there appeared to be no correlation between search effort (i.e. devoted time, number of visited locations, etc.) and the actual outcome. This is a particularly interesting result because, as we later confirm in our third publication [43] with real experiments, the operators' search behavior is clearly different from a more traditional gas plume tracking. Instead, their behavior during our experiments strongly resembled what is known in literature as *infotaxis* [44], an information driven search strategy. That is, the operators were not directly searching for the source, but were instead exploring the environment as to delimit the areas where it was most likely to be until, in the end, there was only one probable location left. The observed behavior can thus be summarized in the traditional 3-stage GSL arrangement as follows:

1. **Detect the target gas**. When the robot starts at a position with no immediate gas readings, the operators explored the environment by

either visiting each of the rooms shown in the navigation map (with no clear preference) or by approaching in sequence the visual indicators (i.e. gas pipes) when they were shown. Overall, this stage was relatively quick as the operators' exploration was very coarse and they usually maxed out the robot's speed. It appears that this exploratory behavior is intrinsic to the human GSL strategy, as it can also been observed in experiments where volunteers with artificially enhanced olfactory capabilities had to track a hidden odor source [99].

2. **Search for the source**. Instead of following the gas distribution gradient, which was often very chaotic because the experiments were conducted indoors (both simulation and real), the observed search behavior continued to be very similar to the first stage. The operators continued to explore very coarsely and sometimes even moved purposefully away from the gas to locations with clean air. After repeated playback and analysis of the recorded experiments, we realized that their goal was not to find the source but to delimit their search area by discarding all unlikely locations. Once they had shrunk down the area of interest, they would change into a slower search where they would pay more attention to the sensor readings (e.g. location of maximum readings) and revisit the visual candidates when shown.

3. **Identification of the source**. For our experiments, we told the operators to either park the robot on the spot where they believed the source to be, or when shown, next to the visual candidate of their choice. In either case, they seemed to choose the most likely location from the last step, which was most of the time right. The only exception that stood out was one scenario where the wind blew the gas quickly away from the source and caused it to accumulate right next to one of the shown candidates. Instead of relying on the anemometer, which would have provided critical information, the operators paid more attention to the gas readings and visual clues instead. One possible explanation of this phenomenon, as discussed in our manuscripts, is that we humans are used to perceiving wind information through physical touch [100, 101, 102] instead of visual representation as in our experiments.

3.3 Dataset of Human-Driven GSL

As mentioned above, we have recorded several experiments of teleoperated GSL for our research. The first batch of these experiments [39] was primarily meant to evaluate how the robot's sensors contribute to the task. It was conducted entirely under simulation to ensure identical test conditions for each run and contains 160 attempts to find the source from 69 volunteer test-operators with no prior training. Whereas the second batch [43] contains 60 experiments that very similar to the first ones in terms of the environment and placement of the source, but repeated under real conditions and with one-time participants. In this case, our goal was to confirm the simulation results with a mobile robot that carries all previously tested sensors, as well as to analyze of the operators' search behavior when they have had no prior training for teleoperated GSL.

For both sets of experiments, we extended the data-collection well beyond the requirements of our research. We recorded all states of the robot (e.g. position, speed, sensor-readings), user input commands (e.g. desired travel direction, explored path, time devoted to decision-making), and (only under simulation) the environment's ground-truth. Furthermore, we conducted a questionnaire before and after the real experiments to inquire about specific aspects we had noticed during the simulated batch. Including, for example, the operators' savviness with teleoperation systems and their perception of the task's difficulty to study whether there is any correlation with their success. Our datasets contain accordingly data that we believe to be highly beneficial for future research on related matters. Such as the development of bio-inspired GSL with machine learning, or as a reference to benchmark autonomous GSL systems against the operators' results. Hence, both dataset sequences along with the questionnaires have been publicly released at `http://mapir.uma.es` for the benefit of the community.

3.A A Robotic Experiment Toward Understanding Human Gas-Source Localization Strategies

Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez

This paper describes an experiment for gas-source localization with a human-teleoperated mobile robot devised to gather data on how humans search for odor-sources. To that end, more than 150 repetitions of the search process are recorded for 69 test subjects, under 4 sensor configurations (including electronic nose, anemometer and video camera) and 4 scenarios (i.e. with different wind-flow conditions and gas-source position). The experiment has been carried out with a ROS-based simulator that allows driving the robot while recording data of interest (e.g. driving commands, robot localization, sensor measurements, ground-truth, etc.) for further analyzing the human process of gas-source searching, and computational fluid dynamics (CFD) to generate realistic and repeatable test conditions. The manuscript describes the different environmental parameters and sensor combinations of the experiment, and explains the methodology under which it was executed. The obtained dataset is publicly available at `http://mapir.isa.uma.es/mapirwebsite/index.php/253-gsl-dataset`.

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3.B Gas Source Localization Strategies for Teleoperated Mobile Robots. An Experimental Analysis

Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez

Gas source localization (GSL) is one of the most important and direct applications of a gas sensitive mobile robot, and consists in searching for one or multiple volatile emission sources with a mobile robot that has improved sensing capabilities (i.e. olfaction, wind flow, etc.). This work adresses GSL by employing a teleoperated mobile robot, and focuses on which search strategy is the most suitable for this teleoperated approach. Four different search strategies, namely chemotaxis, anemotaxis, gas-mapping, and visual-aided search, are analyzed and evaluated according to a set of proposed indicators (e.g. accuracy, efficiency, success rate, etc.) to determine the most suitable one for a human-teleoperated mobile robot. Experimental validation is carried out employing a large dataset composed of over 150 trials where volunteer operators had to locate a gas-leak in a virtual environment under various and realistic environmental conditions (i.e. different wind flow patterns and gas source locations). We report different findings, from which we highlight that, against intuition, visual-aided search is not always the best strategy, but depends on the environmental conditions and the operator's ability to understand how gas distributes.

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3.C Olfactory Telerobotics. A Feasible Solution for Teleoperated Localization of Gas Sources?

Andres Gongora and Javier Gonzalez-Jimenez

Olfactory telerobotics consists in augmenting the sensing capabilities of a teleoperated mobile-robot to acquire information about the surrounding air (i.e. smell, wind-speed, etc.) in addition to the usual audio and video streams. Conceptually, this allows for new and improved applications, among which the most relevant are those related to gas-source localization (GSL). That is, searching through telerobotics for one or multiple gas-emission sources, such as hazardous gas-leaks or the CO_2 signature of trapped survivors in collapsed buildings. Notwithstanding, both the needed sensing-technology for the robot as well as the olfactory feedback-interfaces for the human operator are relatively recent, and might still not meet all the requirements of such applications. This work is therefore meant to assess the current feasibility of olfactory telerobotics to address real-world GSL problems, and accordingly, to determine which aspects play the most important role for its success, or otherwise, might be constraining its usefulness. We have collected to this end a dataset composed of 60 experiments where volunteer operators had to locate and identify hidden gas-source among several identical candidates with an olfaction-enabled robot and under realistic environmental conditions (i.e. uncontrolled and natural gas-distributions). We analyze this data to determine the overall search accuracy and intuitiveness of the system, considering that none of the operators had any prior experience with it, and study the importance of the employed sensory-feedback and how they were employed during the experiments. We finally report different findings, from which we highlight that the tested telerobotics system allowed the operators to correctly identify the source in 3 out of 4 attempts, and that the underlying human search-strategy appears to be a probabilistic-driven behavior that favors semantic and visual information over the robot's gas and wind measurements.

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4 Gas Distribution Mapping

This chapter deals with gas distribution mapping (GDM), a technique that allows an olfaction-enabled robot to generate a spatial representation of the gases around it. We contribute with a new technique that leverages information about wind currents and obstacles in the environment to compute reliable maps from very sparse samples in real-time.

4.1 Introduction

Probably one of the main difficulties for applications that involve gas or airborne particles is the ability to observe their concentration fields. Most chemicals either produce an invisible plume that is hard to detect or, like in the case of dense smoke, prevent vision-based systems from seeing through them. Usually, the only remaining option that can thus measure their concentration are e-noses like the one described in Chapter 2, but whose measurements are restricted to a single spatial location. E-noses can detect and measure the gas intensity, but not provide a simultaneous representation of the whole dispersion by themselves.

However, we can overcome this limitation by combining e-noses with a mathematical model for gas dispersion. By first defining the mathematical rules that determine the sensor readings we would obtain for any position in a given distribution, we can then *reverse* the model to infer the distribution that best explains a set of observations. In this regard, the difficulty of gas distribution mapping becomes the search for a suitable mathematical model.

For instance, one may resort to computational fluid dynamics (CFD) to compute an analytical solution that obeys the laws of fluid-mechanics and provides therefore very accurate results [140, 141]. However, this comes at the expense of a considerable computation load [142] that might limit its usefulness for mobile robotics, where the resources are rather limited. The opposite option is to forego the mathematical model altogether an construct a very simple *memory map* of past observations. But this means that such a map contains no information about unvisited locations and is thus not truly a gas distribution mapping (GDM). A more advanced version of this idea that is still fast to compute includes the Kernel extrapolation method [143], which assumes that nearby locations must be correlated according to a Gaussian distribution and thus provides smooth representation. Similarly, 3D source term estimation [144] is also based on Gaussian-shaped gas distributions, but represents them as perfect gas plumes with analytical solution [145] to predict their value at much farther locations. However, these two last options do not account for obstacles and are thus limited to relatively simple environments (e.g. with large open spaces). Here, the GDM method by Monroy et al. [34] strikes an intermediate balance between computation cost and accuracy, and relies on a Gaussian Markov random field model that also considers how gases interact with obstacles.

But with the exception of CFD, none of the previous methods accounts for one of the key elements that govern gas distributions: dispersion by wind [146]. Because of how wind currents can shape a distribution, having information about them might be even more relevant for GDM than the gas concentration per se. For instance, when you smell a certain aroma, you have considerably more information when you know how the wind blows to reason about where it must be coming from. Some GDM methods have therefore started to combine e-nose's readings with an anemometer, like KDM+V/W [127], an improved version of Kernel extrapolation method that shapes the local gas distribution relative to the wind direction and speed for improved accuracy [31]. But in general, research of GDM methods that integrate wind data has been very reserved in the field of olfactory robotics.

Furthermore, there is yet another shortcoming to GDM: current solutions do, in general, not close the robot's control loop for autonomous applications. That is, most methods process a set of samples to generate a gas map, yet do not tell the robot where to sample next to continue refining their estimates. The difficulty herein is that the robot does not know how the gas is distributed a priori (that is after all the motivation behind GDM) and is thus unable to compute an optimal path from the very beginning. This would force it to dynamically adjust its path as it updates its GDM estimate, and thus, make difficult decisions such as whether to sample at a completely unvisited location or to improve the resolution of the map where it knows that there is gas. As a result, most methods rely on a much simpler patrol-point exploration [127, 34] despite their inherent inefficiency, whereas some exceptions, like an integral method for autonomous GDM and gas source localization (GSL) base on source term estimation [96], take a more advanced approach yet remain limited by the other drawbacks previously listed; like in this case, the need for an obstacle-free environment with relatively homogeneous wind conditions.

4.2 Contribution

To leverage the information provided by the wind yet develop a GDM that is fast enough to compute on a mobile robot, we have combined gas and wind samples under a common Gaussian Markov random field model, aptly named gas-wind GMRF distribution modeling [45]. The relevance of our work is that it also integrates obstacle information for its estimates, which allows for reliable extrapolation event at considerable distances. For instance, if the robot samples gas and wind at one end of a long corridor, and if the air has nowhere else to go, then our method considers that their values must also be similar at the other end. Therefore, when compared to the current state of the art, the advantage of our method is that it allows the robot to make better use of the gas samples is has gathered. Be it to compute GDM maps with fewer data and thus in a shorter period of time, or alternatively, to provide more accurate estimates for the same exploration. Which we have numerically corroborated under simulation using 2D and 3D models of typical environments and GADEN [40], a finite-element computer fluids simulator capable of providing realistic and time-evolving ground-truth for gas distribution.

Still, gas-wind GMRF distribution modeling remains a passive GDM method like most other current approaches. It requires that an external navigation method moves the robot to take samples along the way. Whereas an autonomous GDM solution, on the other hand, should decide its own exploration path and optimize it according to some criteria. Considering the importance of *infotaxis* during our previous human-driven GSL trials (see Chapter 3), we argue that these criteria ought to involve *information gain*. The robot should follow the path that maximizes the amount of new information that is added to its gas map; or in more technical terms, adjust the exploration to achieve the greatest change in entropy between its current estimate and the one expected after moving in a given direction. Also, because the presence of gas and its distribution can not be known in advance, said trajectory must be adjusted dynamically on a case-by-case basis. For instance, the robot might explore an area in a hasty manner while it measures no gas, but it should transition to a more exhaustive behavior once that changes. To accomplish this goal, we have closed gas-wind GMRF distribution modeling's control loop with a Partially Observable Markov Decision Process, a framework that offers a convenient solution to stochastic decision-making problems. The result is a GDM algorithm that can map gas distributions in complex environments just as gas-wind GMRF distribution modeling, but does so in a fully autonomously fashion by gathering gas and wind samples along a quasi-optimal path that minimizes exploration time. We have denoted this algorithm as information-driven gas distribution mapping [46].

4.A Joint Estimation of Gas and Wind Maps for Fast-Response Applications

Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez

This work addresses the problem of 2D gas and wind distribution mapping in real-time with a mobile robot. Our proposal seeks to estimate how gases released in the environment are distributed from a set of sparse gas-concentration and wind-flow measurements; such that by exploiting the high correlation between these two magnitudes we may extrapolate their value for unexplored areas. Furthermore, because the air currents are completely conditioned by the environment, we assume a priori knowledge of static elements such as walls and obstacles when estimating both distribution maps. In particular, this joint estimation problem is modeled as a multivariate Gaussian Markov random field (GMRF), combining gas and wind observations under a common maximum a posteriori estimation problem. It considers two 2D lattices of cells (a scalar gas-concentration field and a wind vector field) which are correlated following the physical laws of gas dispersal and fluid dynamics. Finally, we report various experiments in which our proposal is compared to other gas and gas-wind mapping methods under simulation, with ground-truth generated by a computer fluid-dynamics simulator, as well as under real and uncontrolled conditions.

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4.B Information-Driven Gas Distribution Mapping for Autonomous Mobile Robots

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Javier Monroy, Javier Gonzalez-Jimenez and Alcherio Martinoli

The ability to sense airborne chemicals with mobile robots provides a valuable asset for domains such as industrial safety and environmental monitoring. Often times, this involves detecting how certain gases are spread out in the environment to subsequently prosecute applications that depend on the collected information. But because the majority of the gas-transducers found on mobile robots require physical contact with the analyte, this is usually a slow and laborious exploration to collect measurements from all key locations. In this regard, this paper contributes with a (quasi) optimal exploration algorithm for 2D gas-distribution mapping with autonomous mobile robots. Our proposal combines a Gaussian Markov random field estimator based on gas and wind measurements that is optimized for very sparse sample sizes and indoor environments, with a with a partially observable Markov decision process to close the robot's control loop. The advantage of this approach is that the gas map is not only continuously updated, but can also be leveraged to choose the next location based on how much information it provides. The exploration does consequently adapt to how the gas is distributed during run time, leading to the most efficient path possible and, in turn, providing an accurate gas map with a minimal number of samples. Furthermore, it also accounts for wind-currents in the environment, which improves the reliability of the final gas map even in the presence of obstacles or when the gas distribution diverges from an ideal gas plume. Finally, we report various experiments in simulation, to evaluate our proposal against a computer fluid-dynamics generated ground-truth, as well as under real test-conditions in a wind tunnel.

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2020

5

Smell Recognition

The defining property of electronic noses is their ability to recognize different aromas, however, this usually happens in a very abstract manner. In this chapter, we address this problem and explore the possibilities of teaching an electronic nose to recognize smells according to the subjective human perception.

5.1 Introduction

Let us be blunt: if an electronic nose can not recognize an aroma from its pool of known substances, then it is nothing more a glorified gas detector. Most experiments in the field of olfactory robotics, including those presented in Chapters 3 and 4, assume that the robot can perfectly discern between the substance of interest and all other the aromas in the air. Meaning that these experiments are invariably conducted with a single substance, usually ethanol[1], as a stand-in for generic volatiles. Technically, this assumption is correct, as most gases spread very similarly if they have comparable specific-gravity or when subject to strong wind-currents [207]. However, this thesis would not be complete if we did not train the electronic nose from Chapter 2 for the recognition of smells in addition to measuring their intensity.

[1]Ethanol is convenient for olfactory experiments because it evaporates easily, it is slightly heavier than air and stays close to the floor if undisturbed, it is non-toxic at low concentrations, and it can be easily removed from the environment by venting.

E-noses are often trained to distinguish between subtle variations of a single yet complex smell, like to differentiate between wines [76] or to detect cancer-specific signatures in the breath of patients [208]. But this option might not always be the most suited for olfactory robotics. Unless otherwise dictated by the application, a better option would be to allow the robot's electronic nose to distinguish from a wide range of aromas, even if it comes at the loss of specificity. Much like how we humans communicate that we smell tobacco, for instance, without having to specify the exact blend to understand each other.

Hereof, our goal in this chapter is to train our electronic nose for the recognition of aromas that can be described with simple names. We focus for this task primarily on urban smells because they cover a wide range of characteristics and compounds, and are thus more representative of the generic concept behind *olfaction*. But most importantly, we choose these represent the smells that surround us on our daily lives, ranging from those that are unpleasant (e.g. traffic exhaust) to very pleasant (e.g. flowers and tress).

5.2 Contribution

In order to recognize urban smells with our electronic nose, we first need a dataset of how it responds to each of them, such that we may train some sort of machine learning software to automatically identify any subsequent samples. Naturally, the more variations this data includes, the better the software will learn the *concept* of each smell. Like including samples of an aroma from various sources (e.g. different flowers to learn the concept of *floral*) and different intensities (e.g. a pleasant perfume can become unbearable if too intense), as well as recording them under different ambient conditions to compensate for their effect on the electronic nose's sensors.

Our first work, presented in [47], describes how we obtained exactly such a dataset and how it was processed. We employed a wearable configuration of our electronic nose (see Chapter 2) connected to a smartphone application to record the wearers' perception and label the sensors' response. In total, we collected in this way 10 hours of continuous sensor data with over 600 user entries for 16 smell labels. In addition, we also evaluated in this work several machine learning techniques to determine the most appropriate for our goal. From among the seven tested alternatives, we found that convolutional neural networks, or *Deep Learning*, offered the most reliable results. Lastly, we tried our classifier in a proof of concept application were we generated several automatic smell maps that show the location of smog, fresh air, and other typical urban smells (e.g. areas with many restaurants, gardens, etc.) by pairing he electronic nose with the phone's GPS.

We also used this setup in a second project, published in [48], where we had to detect toxic gases from a chemical spill in Coria del Río, Seville, Spain. For this occasion we added forced air-flow to the electronic nose to improve its response time, and prepended a calibration stage to the convolutional neural networks to compensate for humidity and temperature drift of the sensors. The end result is an odor intensity map of the whole town, which allowed the City Council to evaluate the situation and assess whether their contingency measures were redirecting the gases to a safe area as intended.

5.3 Human-Labeled Smell Dataset

Although the smell dataset we gathered is not the most relevant contribution of this chapter, it remains a cornerstone for the subsequent research. Hereof, one of the main difficulties we found when working on this topic was the lack of data regarding how the sensors respond to different smells. There is obviously a limitation of how useful such data could be if it was recorded with a different to the one that is to be trained, even if they are the exact same model, as sensor-poisoning and aging can change affects their individual characteristics over time [2]. That is, you should only train an electronic nose with readings from its very own sensors.

However, because data is always useful, we contribute with a public dataset of human-labeled smells. It contains the continuous-time recording of all sensors during repeated exposure to complex smells, a user-entered label with a description of said smells, subjective values for their intensity and pleasantness, and the output of auxiliary sensors to measure ambient conditions (temperature, humidity, and pressure) and the location at which the sample was taken. Even if it can not be used to train an electronic nose other than ours, we believe that it is still of value to the scientific community.

5.A Toward the Generation of Smell Maps: Matching Electro-Chemical Sensor Information with Human Odor Perception

Andres Gongora, David Chaves, Alberto Jaenal, Javier Monroy, and Javier Gonzalez-Jimenez

Smell maps are geo-localized representations of the odors present in an environment as perceived by humans. They provide a convenient mean to assess the smellscape of urban areas, determine regions with heavy impact on the population, and measure the reach of industrial emissions. However, their use is not widespread because they are laborious to generate and easily outdated, as they rely on in-place human annotations of the perceived smells. In this work we study the feasibility of automatizing the generation of smell maps by means of a wearable electronic nose (e-nose) as replacement for the human sense of smell; being our main objective the analysis of whether this technology can be employed to map the subjective information inherent in smells. We have collected to that end a dataset composed of more than 450 labeled samples of 10 different smells with a wearable e-nose, and performed a thorough comparison of several machine learning algorithms to evaluate their suitability for this task. As a second contribution, we present a smartphone application developed to record (in situ) e-nose measurements and GPS coordinates as well as the human perception of smells (using a form-based input method). Finally, we present an illustrative example with several automatically generated smell distribution maps and discuss their accuracy.

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5.B Urban Monitoring of Unpleasant Odors with a Handheld Electronic Nose

Andres Gongora, Alberto Jaenal, David Chaves, Javier Monroy, and Javier Gonzalez-Jimenez

This work describes a real application of artificial olfaction where a handheld electronic nose was used as a validation tool for a chemical spillage in a southern town in Spain. The objective was to check if the palliative and precautionary measurements taken by the authorities were working effectively, removing the elevated values of phenol that were detected in a wide area of the municipality of *Coria del Río* (Spain). To this end, a gas distribution map of the affected neighborhoods was built with a portable electronic nose taking into consideration the likely presence of other volatile chemicals in the area. For the latter, we trained a volatile chemical classifier with a dataset of typical urban smells that we wanted to remove from the results (e.g. traffic emissions, garbage, fresh-air), as well as with a specific air-born phenol dataset. Results demonstrated that the palliative measures were in general satisfactory, but some hot-spots were located where the intensity of phenol-like smell was still higher than desired. Advice was given to the local authorities to double-check these locations with analytical gas-monitoring equipment.

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6 Conclusions and Final Thoughts

We are approaching the end of this thesis, so it is time to draw conclusions and think about future research possibilities.

6.1 Conclusions

Olfactory robotics has a remarkable potential to evolve toward all sorts of application fields. By enhancing the sensory capabilities of robots with olfaction, they gain access to a whole new dimension of information about the world that surrounds them. Information that, in turn, allows them to make smarter decisions and achieve a higher degree of autonomy. But like for any other technological advance, this comes at the inevitable cost of new challenges that must be addressed first. In this thesis, akin to the dwarf that stands on the shoulders of a giant, we have built on all the available research that has come before ours to work toward this goal.

First, we have explored the gas-sensing devices known as electronic noses (e-noses) to alleviate some of their shortcomings in Chapter 2. Especially in terms of general versatility for research (e.g. detectable aromas, ease of use) and, more importantly, integration into mobile robots (e.g. portability, communications). One of the main limitations of current e-noses is that they must carry different gas-sensors to detect the volatiles associated with different applications. Making them either bulky and hard to transport on robots, lightweight yet limited to very specific gases and concentrations ranges, or an attempt to balance both requirements that, in practice, satisfies neither.

Because there is no direct solution to this dilemma, not at least with the available gas-sensor technologies, we have designed a modular e-nose that can be assembled using a *building-block* philosophy. That is, instead of carrying all sensors simultaneously, our prototype can be adapted between applications to meet its exact requirements by stacking, as shown in Fig. 6.1, self-contained sensor and ancillary nodes that connect over a shared power and data bus. The key to our design is that none of the nodes is mandatory nor acts as a "master". As soon as power is applied to a given combination of nodes, they automatically start to arbitrate themselves and share information. Gas-sensor nodes will filter and process the raw output from their transducer before they pass on the readings on a common format. So will nodes that host devices such as GPS, thermometers or humidity sensors. And nodes that act as data sinks, like a USB or Bluetooth connection to the robot or an SD memory-card node for data logging, will gather and process said readings as appropriate. The only requirement is that at least one of the nodes acts as a power source. Which, for our prototype, can be provided by the USB connection to the robot or by an optional battery-node meant for wireless operation.

Figure 6.1: The proposed e-nose design allows any desired sensor combination to be assembled using individual nodes, self-contained electronic modules that can be affixed to each other over a shared data and power bus. The modules can be connected in different orientations to account for space constrains or to be placed in an enclosure for easier handling.

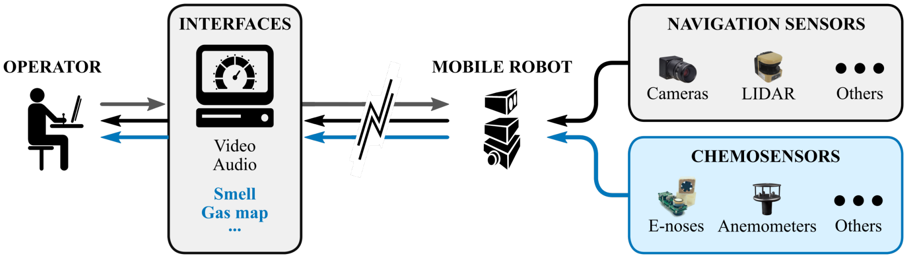

Figure 6.2: Olfactory telepresence control loop. All the robot's sensory information (olfactory or otherwise) is relayed to the human operator, who has full control of the robots actions.

Once we had our e-nose ready, we proceeded to explore with it topics related to mobile robotics as well as hand-held operation. Regarding the former, our first experiments were centered around gas source localization (GSL), one of the most relevant applications for olfactory robotics. Finding the origin of a target volatile is conceptually a simple task that should pose no challenge for an autonomous robot. But the complex nature of how gases distribute in free space, especially in the presence of turbulent airflow that carries the gas-particles away from the source, is so far preventing all research efforts from achieving a generic solution for real-world settings [13]. For this reason, rather than developing a new autonomous technique, we have taken a step back and approached GSL in Chapter 3 from the perspective of gas-sensitive teleoperation with a setup shown in Fig. 6.2. Although this approach was very different from what is considered "common" in olfactory robotics, it allowed us to confirm that humans can find the origin of a gas-emission when provided with the very same information a robot has at its disposal. Proving, in turn, that it is indeed possible to develop a completely autonomous GSL algorithm. Hence, our teleoperated approach offers a temporal solution for critical GSL application (e.g. industrial accidents) where current algorithms would be too risky, and also, serves as a platform to study the human search behavior (shown in this thesis to be akin to infotaxis) for the future development of robust autonomous GSL.

Our second focus for olfactory robotics was on gas distribution mapping (GDM). This process allows a robot to estimate how an aroma or volatile is spread out in its work environment from a set of sparse measurements, usually comprised of gas observations (e.g. from the robot's e-nose) and, in some cases, wind data from an anemometer. So far, several GDM approaches haven been proposed for mobile robotics as seen in Chapter 4, all of which have one common characteristic. They must work in real-time, or as close as possible to it, to provide the robot with a continuously updated map that accounts for the latest gas measurements. Especially for applications like industrial safety, where fast decision making is paramount and computational fluid dynamics

(CFD) simulations would be too slow to compute. As a result, the current state of the art of GDM algorithms greatly favors computation speed over accuracy. But in doing so, self-limit their ability to make predictions about the gas distribution at remote locations that were not subject to sampling. The method we propose in this thesis, *GW-GMRF*, on the other hand, combines all the information the robot has at its disposal, including gas samples, wind observation, and knowledge about obstacles, to compute a more accurate gas distribution map. This leads to a formulation that is still real-time computable but slower, yet provides reliable gas maps with a fraction of the otherwise required gas and wind observations. Meaning that, although the robot has to spend slightly more computation resources on *GW-GMRF*, the net amount of exploration and time it has to spend in a given environment is substantially reduced when compared to the available alternatives.

Finally, in Chapter 5 we have exploited our e-nose's ability to be operated in a portable configuration when connected to a smartphone. Our goal was to collect a dataset of common urban smells so that we could train the e-nose to recognize them and, in end effect, provide robots with more semantic information about their surroundings. As an intermediate step and proof of concept of this idea, we have employed our e-nose for automatic *smellwalking* in our city, that is, mapping the geographical location of smells, and to study the distribution of gases associated to a chemical spill in a nearby town. In both cases, we paired each recognized smell with the GPS coordinates (obtained from the smartphone) of its sample location, which leads to relatively simplistic smell maps (see Fig. 6.3). But in principle, there is nothing that would prevent us from combining this smells recognition with our GDM method as we discuss later during our intended future work.

Figure 6.3: Simple smell map of Malaga's port and sea promenade created with our e-nose and a GPS-enabled smartphone. The colored markers show locations where training data was taken, whereas the colored path shows automatically generated smell labels. In this case, both the training data and output are for the same general area, but once trained, the e-nose can also recognize smells in new places or provide information to a robot for tasks like GSL or GDM.

As for the contributions of this thesis, we can summarize our results into the following key conclusions:

- **Electronic noses**. Modular e-noses are a viable alternative to current commercial solutions. Their design certainly incurs into unneeded duplication of electronic components, as each sensor-nodes must now carry the complete circuitry to handle their individual sensors and can no longer share it. However, this brings not only versatility and reusability to the design of e-noses, but also reduces development costs and ensures long-term serviceability, as new sensor-nodes can be easily added when needed.

- **Gas source localization**. For complex and critical scenarios, teleoperation has demonstrated to be a feasible solution for GSL application. Our results have also shown that the human operators, which manage to find the source without prior training, rely on a search technique akin to infotaxis. Instead of following the gas gradient back to its origin, they explore the environment until the possible locations of the source are reduced to a single, very likely location. Although more experiments are required to generalize this conclusion, in our scenario most operators managed to find the gas source with this strategy even when the robot was only equipped with an e-nose and there was no semantic information available (i.e. no locations of particular interest).

- **Gas distribution mapping**. In this thesis, we have presented *GW-GMRF*, a new probabilistic GDM method that accounts for wind-flow modeling to provide accurate estimates. Despite its computational overhead when compared with other similar real-time solutions, the presented method is able to generate reliable maps with a fraction of the data samples. This, in addition to its statistically significant uncertainty, make *GW-GMRF* an excellent choice for fast-response applications where a robot is unable to gather much data before having to make a decision. Furthermore, *GW-GMRF* can operate fully autonomously using our *IGDM* algorithm, allowing it to take control of the robot and create a gas map of the environment in the shortest possible time by following a dynamic, quasi-optimal exploration path.

- **Automatic smell recognition**. We have matched the response of e-noses to the human-subjective perception of smells, which could potentially provide an autonomous robot with additional semantic information. In our case scenarios, our e-nose recognized the pleasantness of the air in urban areas, and combined with GPS, it assessed the spatial reach of a toxic spill. As a parallel contribution, we have also published the manually-labeled smell-dataset with which we have trained the classifier.

All in all, there is still a long path ahead of olfactory robotics. Maybe, one day, it will be as good or even surpass our mammal sense of smell. But research must for now focus on solving one problem at a time. The major liming factor at present is the available transducers for e-noses. They determine how small an e-nose can be (whilst being portable on a robot) and the range of gases it can detect. But even if we had perfect gas sensors readily available by tomorrow, we would still have to develop the algorithms that can make efficient use of them. In this thesis, we have contributed precisely to this goal. Although we might not have completely solved any particular problem, we believe that our work constitutes one more step in this collaborative effort that pursues robots that are indistinguishable from nature.

Future work

As is always the case for any project, there are many other interesting research lines that could not be covered by this thesis. Some of the most interesting ones are outlined below.

Smell localization and mapping. The combination of automatic smell recognition (Chapter 5) for GSL (Chapter 3) and/or GDM (Chapter 4) is the next logical step for an olfaction-enabled robot. Implementing such a solution should be relatively simple, as the robot would only have to recognize the smell it is looking for and then use its *perceived intensity* (i.e. how strong it smells) in place of a gas concentration as the input for the subsequent algorithms. A much more interesting challenge is, therefore, the simultaneous tracking of multiple odors in the environment. For example, the robot could leverage the information it has already gathered while searching for the origin of a specific smell to greatly accelerate the search for a second, completely different smell.

Variable resolution for gas distribution mapping. Our GDM method employs a fixed resolution, which implies that wide areas with no gas, and thus of little interest, require the same amount of computation than those with gas. This, in turn, limits the resolution of the estimated gas map because the robot's resources can not handle high resolutions. Therefore, a gas map with variable resolution would (i) greatly reduce the computational requirements for locations with no gas and (ii) provide more detail for those with gas. Yet implementing this on our GDM method (Chapter 4) is not trivial, as the number of cells and connections in the Markov field would have to adapt dynamically to produce the desired resolution change.

Bio-inspired GSL. We have gathered a significant dataset while researching GSL in the context of teleoperation. One possible use for this data is the development of a new bio-inspired GSL technique by training some sort of machine-learning technique to emulate the human search-behavior. In the case that this data is not enough to train a new algorithm by itself, we can also take a more heuristic approach and leverage that said behavior is very akin to infotaxis, as previously described.

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Bibliography

[1] Yousif Albastaki and Fatema Albalooshi. *Electronic nose technologies and advances in machine olfaction*. IGI Global, 2018.

[2] Tim C Pearce, Susan S Schiffman, H Troy Nagle, and Julian W Gardner. *Handbook of machine olfaction: e-nose technology*. J. Wiley & Sons, 2006.

[3] Krishna Persaud and George Dodd. Analysis of discrimination mechanisms in the mammalian olfactory system using a model nose. *Nature*, 299(5881):352–355, 1982.

[4] Nathan S Lewis. Comparisons between mammalian and artificial olfaction based on arrays of carbon black- polymer composite vapor detectors. *Accounts of chemical research*, 37(9):663–672, 2004.

[5] Andreas T Guentner, Vitaly Koren, Kiran Chikkadi, Marco Righettoni, and Sotiris E Pratsinis. E-nose sensing of low-ppb formaldehyde in gas mixtures at high relative humidity for breath screening of lung cancer? *ACS Sensors*, 1(5):528–535, 2016.

[6] Javier G. Monroy, Achim J. Lilienthal, Jose-Luis Blanco, Javier Gonzalez-Jimenez, and Marco Trincavelli. Probabilistic gas quantification with {MOX} sensors in open sampling systems—a gaussian process approach. *Sensors and Actuators B: Chemical*, 188:298–312, 2013.

[7] Frank Röck, Nicolae Barsan, and Udo Weimar. Electronic nose: current status and future trends. *Chemical reviews*, 108(2):705–725, 2008.

[8] Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez. An electronic architecture for multipurpose artificial noses. *Journal of Sensors*, 2018, 2018.

[9] Javier Gonzalez-Jimenez, Javier Monroy, and Jose-Luis Blanco. The multi-chamber electronic nose–an improved olfaction sensor for mobile robotics. *Sensors*, 11(6):6145–6164, jun 2011.

[10] Maximilian Lackner. Tunable diode laser absorption spectroscopy (tdlas) in the process industries–a review. *Reviews in Chemical Engineering*, 23(2):65–147, 2007.

[11] Marco Trincavelli, Victor Hernandez Bennetts, and Achim J Lilienthal. A least squares approach for learning gas distribution maps from a set of integral gas concentration measurements obtained with a tdlas sensor. In *SENSORS, 2012 IEEE*, pages 1–4. IEEE, 2012.

[12] Victor Manuel Hernandez Bennetts, Achim J Lilienthal, Ali Abdul Khaliq, Víctor Pomareda Sesé, and Marco Trincavelli. Towards real-world gas distribution mapping and leak localization using a mobile robot with 3d and remote gas sensing capabilities. In *Robotics and Automation (ICRA), 2013 IEEE International Conference on*, pages 2335–2340. IEEE, 2013.

[13] Lei Shu, Mithun Mukherjee, Xiaoling Xu, Kun Wang, and Xiaoling Wu. A survey on gas leakage source detection and boundary tracking with wireless sensor networks. *Ieee Access*, 4:1700–1715, 2016.

[14] Gabriele Ferri, Emanuele Caselli, Virgilio Mattoli, Alessio Mondini, Barbara Mazzolai, and Paolo Dario. SPIRAL: A novel biologically-inspired algorithm for gas/odor source localization in an indoor environment with no strong airflow. *Robotics and Autonomous Systems*, 57(4):393–402, 2009.

[15] Patrick P Neumann, Victor Hernandez Bennetts, Achim J Lilienthal, Matthias Bartholmai, and Jochen H Schiller. Gas source localization with a micro-drone using bio-inspired and particle filter-based algorithms. *Advanced Robotics*, 27(9):725–738, 2013.

[16] Achim Lilienthal. *Gas Distribution Mapping and Gas Source Localisation with a Mobile Robot.* Logos Verlag Berlin, 2005.

[17] Andreas Kroll, Werner Baetz, and Daniel Peretzki. On autonomous detection of pressured air and gas leaks using passive ir-thermography for mobile robot application. In *2009 IEEE International Conference on Robotics and Automation*, pages 921–926. IEEE, 2009.

[18] Gero Bonow and Andreas Kroll. Gas leak localization in industrial environments using a tdlas-based remote gas sensor and autonomous mobile robot with the tri-max method. In *2013 IEEE International Conference on Robotics and Automation*, pages 987–992. IEEE, 2013.

[19] Samuel Soldan, Jochen Welle, Thomas Barz, Andreas Kroll, and Dirk Schulz. Towards autonomous robotic systems for remote gas leak detection and localization in industrial environments. In *Field and Service Robotics*, pages 233–247. Springer, 2014.

[20] Masaru Shimizu, Masayuki Okugawa, Katsuji Oogane, Yoshikazu Ohtsubo, Tetsuya Kimura, Tomoichi Takahashi, and Satoshi Tadokoro. Standard rescue tasks based on the japan virtual robotics challenge. In *Robot World Cup*, pages 440–451. Springer, 2016.

[21] Gideon Kowadlo and R Andrew Russell. Robot odor localization: a taxonomy and survey. *The International Journal of Robotics Research*, 27(8):869–894, 2008.

[22] Nyayu Latifah Husni, Ade Silvia, Siti Nurmaini, and Irsyadi Yani. Odor localization sub tasks: A survey. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, 8(3):101–105, 2016.

[23] Behzad Bayat, Naveena Crasta, Alessandro Crespi, António M Pascoal, and Auke Ijspeert. Environmental monitoring using autonomous vehicles: a survey of recent searching techniques. *Current opinion in biotechnology*, 45:76–84, 2017.

[24] Boris I Shraiman and Eric D Siggia. Scalar turbulence. *Nature*, 405(6787):639–646, 2000.

[25] Mikel Vuka, Erik Schaffernicht, Michael Schmuker, Victor Hernandez Bennetts, Francesco Amigoni, and Achim J Lilienthal. Exploration and localization of a gas source with mox gas sensors on a mobile robot—a gaussian regression bout amplitude approach. In *Olfaction and Electronic Nose (ISOEN), 2017 ISOCS/IEEE International Symposium on*, pages 1–3. IEEE, 2017.

[26] Yuta Wada, Haruka Matsukura, and Hiroshi Ishida. Estimation of gas source location from fluctuating readings of gas sensors and anemometer on mobile robot in outdoor environment. *ECS Transactions*, 75(16):99–106, 2016.

[27] Faezeh Rahbar, Ali Marjovi, Pierre Kibleur, and Alcherio Martinoli. A 3-d bio-inspired odor source localization and its validation in realistic environmental conditions. In *Intelligent Robots and Systems (IROS), 2017 IEEE/RSJ International Conference on*, pages 3983–3989. IEEE, 2017.

[28] Carlos Sanchez-Garrido, Javier Monroy, and Javier Gonzalez-Jimenez. Probabilistic estimation of the gas source location in indoor environments by combining gas and wind observations. In *Int. Conference on Applications of Intelligent Systems (APPIS)*, 2018.

[29] Wataru Tsujita, Akihito Yoshino, Hiroshi Ishida, and Toyosaka Moriizumi. Gas sensor network for air-pollution monitoring. *Sensors and Actuators, B: Chemical*, 110(2):304–311, 2005.

[30] Jes Fenger. Urban air quality. *Atmospheric environment*, 33(29):4877–4900, 1999.

[31] Patrick P Neumann, Sahar Asadi, Achim J Lilienthal, Matthias Bartholmai, and Jochen H Schiller. Autonomous gas-sensitive microdrone: Wind vector estimation and gas distribution mapping. *IEEE robotics & automation magazine*, 19(1):50–61, 2012.

[32] Victor Hernandez Bennetts, Erik Schaffernicht, Todor Stoyanov, Achim J Lilienthal, and Marco Trincavelli. Robot assisted gas tomography—localizing methane leaks in outdoor environments. In *2014 IEEE International Conference on Robotics and Automation (ICRA)*, pages 6362–6367. IEEE, 2014.

[33] Matteo Reggente and Achim J. Lilienthal. The 3d-kernel dm+v/w algorithm: Using wind information in three dimensional gas distribution modelling with a mobile robot. In *IEEE Sensors*, pages 999–1004, 2010.

[34] Javier G. Monroy, Jose Luis Blanco, and Javier Gonzalez-Jimenez. Time-variant gas distribution mapping with obstacle information. *Autonomous Robots*, 40(1):1–16, 2016.

[35] M García, M Aleixandre, J Gutiérrez, and MC Horrillo. Electronic nose for wine discrimination. *Sensors and Actuators B: Chemical*, 113(2):911–916, 2006.

[36] Ramon Aparicio, Silvia M Rocha, Ivonne Delgadillo, and María Teresa Morales. Detection of rancid defect in virgin olive oil by the electronic nose. *Journal of agricultural and food chemistry*, 48(3):853–860, 2000.

[37] Xiao Liu, Sitian Cheng, Hong Liu, Sha Hu, Daqiang Zhang, and Huansheng Ning. A survey on gas sensing technology. *Sensors*, 12(7):9635–9665, 2012.

[38] Javier Monroy, Francisco Melendez-Fernandez, Andres Gongora, and Javier Gonzalez-Jimenez. Integrating olfaction in a robotic telepresence loop. In *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, pages 1012–1017. IEEE, 2017.

[39] Andres Gongora, Javier G Monroy, and Javier Gonzalez-Jimenez. A robotic experiment toward understanding human gas-source localization strategies. In *2017 ISOCS/IEEE International Symposium on Olfaction and Electronic Nose (ISOEN)*, pages 1–3. IEEE, 2017.

[40] Javier Monroy, Victor Hernandez-Bennetts, Han Fan, Achim Lilienthal, and Javier Gonzalez-Jimenez. GADEN: a 3D gas dispersion simulator for mobile robot olfaction in realistic environments. *MDPI Sensors*, 17(7: 1479):1–16, 2017.

[41] Javier Monroy, Jose-Luis Blanco, and Javier Gonzalez-Jimenez. Time-variant gas distribution mapping with obstacle information. *Autonomous Robots*, 40(1):1–16, 2016.

[42] Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez. Gas source localization strategies for teleoperated mobile robots. an experimental analysis. In *2017 European Conference on Mobile Robots (ECMR)*, pages 1–6. IEEE, 2017.

[43] Andres Gongora and Javier Gonzalez-Jimenez. Olfactory telerobotics. a feasible solution for teleoperated localization of gas sources? *Robotics and Autonomous Systems*, 113:1–9, 2019.

[44] Massimo Vergassola, Emmanuel Villermaux, and Boris I Shraiman. 'infotaxis' as a strategy for searching without gradients. *Nature*, 445(7126):406–409, 2007.

[45] Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez. Joint estimation of gas & wind maps for fast-response applications. *Applied Mathematical Modelling*, 2020.

[46] Andres Gongora, Faezeh Rahbar, Chiara Ercolani, Javier Monroy, Javier Gonzalez-Jimenez, and Alcherio Martinoli. Information-driven gas distribution mapping for autonomous mobile robots. *Submitted to scientific journal and under review)*, 2020.

[47] Andres Gongora, David Chaves, Alberto Jaenal, Javier Gonzalez Monroy, and Javier González Jiménez. Toward the generation of smell maps: Matching electro-chemical sensor information with human odor perception. In *APPIS*, pages 134–145, 2018.

[48] Andres Gongora, Alberto Jaenal, David Chaves, Javier Monroy, and Javier Gonzalez-Jimenez. Urban monitoring of unpleasant odors with a handheld electronic nose. pages 1–3, 2019.

[49] Seo Yun Park, Yeonhoo Kim, Taehoon Kim, Tae Hoon Eom, Soo Young Kim, and Ho Won Jang. Chemoresistive materials for electronic nose: Progress, perspectives, and challenges. *Infomat*, 2019.

[50] Shaoqing Cui, Jun Wang, Liangcheng Yang, Jianfeng Wu, and Xinlei Wang. Qualitative and quantitative analysis on aroma characteristics of ginseng at different ages using e-nose and gc–ms combined with chemometrics. *Journal of pharmaceutical and biomedical analysis*, 102:64–77, 2015.

[51] Martin Längkvist and Amy Loutfi. Unsupervised feature learning for electronic nose data applied to bacteria identification in blood. In *NIPS 2011 workshop on deep learning and unsupervised feature learning*, 2011.

[52] Martin Längkvist, Lars Karlsson, and Amy Loutfi. A review of unsupervised feature learning and deep learning for time-series modeling. *Pattern Recognition Letters*, 42:11–24, 2014.

[53] Pai Peng, Xiaojin Zhao, Xiaofang Pan, and Wenbin Ye. Gas classification using deep convolutional neural networks. *Sensors*, 18(1):157, 2018.

[54] Yu-Hsuan Liao, Zhong-Chuang Wang, Fu-Gui Zhang, Maysam F Abbod, Chung-Hung Shih, and Jiann-Shing Shieh. Machine learning methods applied to predict ventilator-associated pneumonia with pseudomonas aeruginosa infection via sensor array of electronic nose in intensive care unit. *Sensors*, 19(8):1866, 2019.

[55] Peter Hauptmann. *Sensors: principles and applications.* Prentice-Hall, Inc., 1993.

[56] JW Gardner. Microsensors-principles and applications, 1994.

[57] DS Ballantine Jr, Robert M White, Stephen J Martin, Antonio J Ricco, ET Zellers, GC Frye, and H Wohltjen. *Acoustic wave sensors: theory, design and physico-chemical applications.* Elsevier, 1996.

[58] Electronic Noses. Principles and applications, jw gardner, pn bartlett, 1999.

[59] Kiyoshi Toko. *Biomimetic sensor technology.* Cambridge University Press, 2000.

[60] Javier G Monroy, Achim Lilienthal, Jose Luis Blanco, Javier González-Jimenez, and Marco Trincavelli. Calibration of mox gas sensors in open sampling systems based on gaussian processes. In *SENSORS, 2012 IEEE*, pages 1–4. IEEE, 2012.

[61] Javier Monroy, Javier Gonzalez-Jimenez, and José-Luis Blanco. Overcoming the slow recovery of mox gas sensors through a system modeling approach. *Sensors*, 12(10):13664–13680, oct 2012.

[62] Lorenz Meier, J Camacho, B Godbolt, J Goppert, L Heng, M Lizarraga, et al. Mavlink: Micro air vehicle communication protocol. *Online]. Tillgänglig: http://qgroundcontrol. org/mavlink/start.[Hämtad 2014-05-22]*, 2013.

[63] F. K. Che Harun, J. E. Taylor, J. A. Covington, and J. W. Gardner. An electronic nose employing dual-channel odour separation columns with large chemosensor arrays for advanced odour discrimination. *Sensors and Actuators, B: Chemical*, 141(1):134–140, 2009.

[64] Martin O'hara. *EMC at Component and PCB Level.* Elsevier, 1998.

[65] M Keith Armstrong. Pcb design techniques for lowest-cost emc compliance. part 1 & 2. *Electronics & communication engineering journal*, 11(4):185–194, 1999.

[66] Elizabeth Bales, Nima Nikzad, Nichole Quick, Celal Ziftci, Kevin Patrick, and William Griswold. Citisense: Mobile air quality sensing for individuals and communities design and deployment of the citisense mobile air-quality system. In *Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2012 6th International Conference on*, pages 155–158. IEEE, 2012.

[67] Javier G Monroy, Javier Gonzalez-Jimenez, and Carlos Sanchez-Garrido. Monitoring household garbage odors in urban areas through distribution maps. In *IEEE SENSORS 2014 Proceedings*, pages 1364–1367. IEEE, 2014.

[68] Andrey Somov, Alexander Baranov, Denis Spirjakin, Andrey Spirjakin, Vladimir Sleptsov, and Roberto Passerone. Deployment and evaluation of a wireless sensor network for methane leak detection. *Sensors and Actuators A: Physical*, 202:217–225, 2013.

[69] Patrick P Neumann, Victor Hernandez Bennetts, Achim J Lilienthal, and Matthias Bartholmai. From insects to micro air vehicles—a comparison of reactive plume tracking strategies. In *Intelligent Autonomous Systems 13*, pages 1533–1548. Springer, 2016.

[70] Hossein Rezaei Estakhroueiyeh and Esmat Rashedi. Detecting moldy bread using an e-nose and the knn classifier. In *Computer and Knowledge Engineering (ICCKE), 2015 5th Int. Conference on*, pages 251–255. IEEE, 2015.

[71] Amy Loutfi, Silvia Coradeschi, Ganesh Kumar Mani, Prabakaran Shankar, and John Bosco Balaguru Rayappan. Electronic noses for food quality: A review. *Journal of Food Engineering*, 144:103–111, 2015.

[72] S Chatterjee, M Castro, and Jean-François Feller. An e-nose made of carbon nanotube based quantum resistive sensors for the detection of eighteen polar/nonpolar voc biomarkers of lung cancer. *Journal of Materials Chemistry B*, 1(36):4563–4575, 2013.

[73] Marcel Bruins, Zeaur Rahim, Albert Bos, Wendy WJ van de Sande, Hubert Ph Endtz, and Alex van Belkum. Diagnosis of active tuberculosis by e-nose analysis of exhaled air. *Tuberculosis*, 93(2):232–238, 2013.

[74] K Brudzewski, S Osowski, and W Pawlowski. Metal oxide sensor arrays for detection of explosives at sub-parts-per million concentration levels by the differential electronic nose. *Sensors and Actuators B: Chemical*, 161(1):528–533, 2012.

[75] Jon R Askim, Zheng Li, Maria K LaGasse, Jaqueline M Rankin, and Kenneth S Suslick. An optoelectronic nose for identification of explosives. *Chemical Science*, 7(1):199–206, 2016.

[76] Seung-Joo Lee and Ann C Noble. Characterization of odor-active compounds in californian chardonnay wines using gc-olfactometry and gc-mass spectrometry. *Journal of Agricultural and Food Chemistry*, 51(27):8036–8044, 2003.

[77] Sandra Van den Velde, Frederik Nevens, Daniel van Steenberghe, Marc Quirynen, et al. Gc–ms analysis of breath odor compounds in liver patients. *Journal of Chromatography B*, 875(2):344–348, 2008.

[78] Keith J Albert, Nathan S Lewis, Caroline L Schauer, Gregory A Sotzing, Shannon E Stitzel, Thomas P Vaid, and David R Walt. Cross-reactive chemical sensor arrays. *Chemical reviews*, 100(7):2595–2626, 2000.

[79] Alphus D Wilson and Manuela Baietto. Applications and advances in electronic-nose technologies. *Sensors*, 9(7):5099–5148, 2009.

[80] William J Buttner, Matthew B Post, Robert Burgess, and Carl Rivkin. An overview of hydrogen safety sensors and requirements. *International Journal of Hydrogen Energy*, 36(3):2462–2470, 2011.

[81] S De Vito, E Massera, L Quercia, and G Di Francia. Analysis of volcanic gases by means of electronic nose. *Sensors and Actuators B: Chemical*, 127(1):36–41, 2007.

[82] Carlos Sanchez-Garrido, Javier Monroy, and Javier Gonzalez-Jimenez. A configurable smart e-nose for spatio-temporal olfactory analysis. In *IEEE Sensors*, pages 1968–1971, 2014.

[83] Jeffrey A Dickson and Rodney M Goodman. Integrated chemical sensors based on carbon black and polymer films using a standard cmos process and post-processing. In *Circuits and Systems, 2000. Proceedings. ISCAS 2000 Geneva. The 2000 IEEE International Symposium on*, volume 4, pages 341–344. IEEE, 2000.

[84] M Holmberg and T Artursson. Drift compensation, standards, and calibration methods. *Handbook of Machine Olfaction: Electronic Nose Technology*, pages 325–346, 2002.

[85] KR Kashwan and M Bhuyan. Robust electronic-nose system with temperature and humidity drift compensation for tea and spice flavour discrimination. In *2005 Asian Conference on sensors and the International Conference on New Techniques in Pharmaceutical and Biomedical Research*, pages 154–158. IEEE, 2005.

[86] Lorenz Meier, Petri Tanskanen, Friedrich Fraundorfer, and Marc Pollefeys. Pixhawk: A system for autonomous flight using onboard computer vision. In *Robotics and automation (ICRA), 2011 IEEE international conference on*, pages 2992–2997. IEEE, 2011.

[87] Andrew P Lee and Brian J Reedy. Temperature modulation in semiconductor gas sensing. *Sensors and Actuators B: Chemical*, 60(1):35–42, 1999.

[88] SC Chang, JR Stetter, and CS Cha. Amperometric gas sensors. *Talanta*, 40(4):461–477, 1993.

[89] C Palacios, JG Monroy, J Gonzalez-Jimenez, J Olalla, and Antonio J Moyano. Monitorización y control de la emisión de olores en instalaciones de aguas residuales: Proyecto sulfscan. In *III Conferencia Internacional Sobres Gestión de Olores en el Medio Ambiente, Bilbao, España, http://www. olores. org*, 2016.

[90] Alphasense Ltd. *AAN 010: Design considerations in gas detector sampling*.

[91] Hiroshi Ishida, Takashi Ushiku, Shigeki Toyama, Haruki Taniguchi, and Toyosaka Moriizumi. Mobile robot path planning using vision and olfaction to search for a gas source. In *IEEE Sensors, 2005.*, pages 4–pp. IEEE, 2005.

[92] David Hasenfratz. *Enabling Large-Scale Urban Air Quality Monitoring with Mobile Sensor Nodes*. PhD thesis, Diss., Eidgenössische Technische Hochschule ETH Zürich, Nr. 22481, 2015.

[93] Alexandre Perera, Teodor Sundic, Antonio Pardo, Ricardo Gutierrez-Osuna, and Santiago Marco. A portable electronic nose based on embedded pc technology and gnu/linux: hardware, software and applications. *IEEE Sensors Journal*, 2(3):235–246, 2002.

[94] Ali Marjovi and Lino Marques. Optimal spatial formation of swarm robotic gas sensors in odor plume finding. *Autonomous Robots*, 35(2-3):93–109, 2013.

[95] Thomas Lochmatter and Alcherio Martinoli. Theoretical analysis of three bio-inspired plume tracking algorithms. In *2009 IEEE International Conference on Robotics and Automation*, pages 2661–2668. IEEE, 2009.

[96] Faezeh Rahbar, Ali Marjovi, and Alcherio Martinoli. Design and performance evaluation of an algorithm based on source term estimation for odor source localization. *Sensors*, 19(3):656, 2019.

[97] Thomas Lochmatter and Alcherio Martinoli. Tracking odor plumes in a laminar wind field with bio-inspired algorithms. In *Experimental robotics*, pages 473–482. Springer, 2009.

[98] Javier Monroy, J. R. Ruiz-Sarmiento, and Javier Gonzalez-Jimenez. An evaluation of plume tracking as a strategy for gas source localization in turbulent wind flows. In *ISOCS/IEEE International Symposium on Olfaction and Electronic Nose (ISOEN)*, may 2019.

[99] Haruka Matsukura, Hironori Hashiguchi, and Hiroshi Ishida. Tracking of a gas plume with the aid of olfactory assist mask. *IEEE Sensors Journal*, 17(16):5332–5340, 2017.

[100] Taeyong Moon and Gerard J Kim. Design and evaluation of a wind display for virtual reality. In *Proceedings of the ACM symposium on Virtual reality software and technology*, pages 122–128. ACM, 2004.

[101] Sandip Kulkarni, Charles Fisher, Eric Pardyjak, Mark Minor, and John Hollerbach. Wind display device for locomotion interface in a virtual environment. In *World Haptics 2009-Third Joint EuroHaptics conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*, pages 184–189. IEEE, 2009.

[102] Haruka Matsukura, Tatsuhiro Yoneda, and Hiroshi Ishida. Smelling screen: development and evaluation of an olfactory display system for presenting a virtual odor source. *IEEE transactions on visualization and computer graphics*, 19(4):606–615, 2013.

[103] Amy Loutfi, Silvia Coradeschi, Achim J Lilienthal, and Javier Gonzalez. Gas distribution mapping of multiple odour sources using a mobile robot. *Robotica*, 27(02):311–319, 2009.

[104] Victor Hernandez Bennetts, Erik Schaffernicht, Victor Pomareda, Achim J Lilienthal, Santiago Marco, and Marco Trincavelli. Combining non selective gas sensors on a mobile robot for identification and mapping of multiple chemical compounds. *Sensors*, 14(9):17331–17352, 2014.

[105] J Norberto Pires, Cosimo Distante, Giovanni Indiveri, and Giulio Reina. An application of mobile robotics for olfactory monitoring of hazardous industrial sites. *Industrial Robot: An Int. Journal*, 36(1):51–59, 2009.

[106] Martin Saska, Jan Langr, and Libor Přeučil. Plume tracking by a self-stabilized group of micro aerial vehicles. In *International Workshop on Modelling and Simulation for Autonomous Systems*, pages 44–55. Springer, 2014.

[107] Richard Held and Alan Hein. Movement-produced stimulation in the development of visually guided behavior. *Journal of comparative and physiological psychology*, 56(5):872, 1963.

[108] Morgan Quigley, Ken Conley, Brian P. Gerkey, Josh Faust, Tully Foote, Jeremy Leibs, Rob Wheeler, and Andrew Y. Ng. ROS: an open-source Robot Operating System. In *ICRA Workshop on Open Source Software*, 2009.

[109] Terrence Fong and Charles Thorpe. Vehicle teleoperation interfaces. *Autonomous robots*, 11(1):9–18, 2001.

[110] L Srinivasavaradhan, G Chandramouli, and AG Maniprashanna. 7 th sense. a multipurpose robot for military. In *Perspective Technologies and Methods in MEMS Design, 2009. MEMSTECH 2009. 2009 5th International Conference on*, pages 158–160. IEEE, 2009.

[111] Tetsushi Kamegawa, T Yarnasaki, Hiroki Igarashi, and Fumitoshi Matsuno. Development of the snake-like rescue robot" kohga". In *Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference on*, volume 5, pages 5081–5086. IEEE, 2004.

[112] Pawel Pyk, Sergi Bermúdez i Badia, Ulysses Bernardet, Philipp Knüsel, Mikael Carlsson, Jing Gu, Eric Chanie, Bill S Hansson, Tim C Pearce, and Paul FMJ Verschure. An artificial moth: Chemical source localization using a robot based neuronal model of moth optomotor anemotactic search. *Autonomous Robots*, 20(3):197–213, 2006.

[113] Olivier Rochel, Dominique Martinez, Etienne Hugues, and Frédéric Sarry. Stereo-olfaction with a sniffing neuromorphic robot using spiking neurons. In *16th European Conf. on Solid-State Transducers*, pages 4–p, 2002.

[114] Hiroshi Ishida. Robotic systems for gas/odor source localization: Gap between experiments and real-life situations. In *Proc. IEEE Int. Conf. on Robotics and Automation, 2007. (ICRA 2007)*, pages 3–8, 2007.

[115] Lino Marques, Urbano Nunes, and Anibal T de Almeida. Olfaction-based mobile robot navigation. *Thin solid films*, 418(1):51–58, 2002.

[116] Ji-Gong Li, Qing-Hao Meng, Yang Wang, and Ming Zeng. Odor source localization using a mobile robot in outdoor airflow environments with a particle filter algorithm. *Autonomous Robots*, 30(3):281–292, 2011.

[117] Hiroshi Ishida, Hidenao Tanaka, Haruki Taniguchi, and Toyosaka Moriizumi. Mobile robot navigation using vision and olfaction to search for a gas/odor source. In *Intelligent Robots and Systems, 2004.(IROS 2004). Proc. 2004 IEEE/RSJ Int. Conf.*, volume 1, pages 313–318. IEEE, 2004.

[118] Ping Jiang, Qing-Hao Meng, and Ming Zeng. Mobile robot gas source localization via top-down visual attention mechanism and shape analysis. In *Intelligent Control and Automation (WCICA), 2010 8th World Congress on*, pages 1818–1823. IEEE, 2010.

[119] Francisco Melendez-Fernandez, Cipriano Galindo, and Javier Gonzalez-Jimenez. A web-based solution for robotic telepresence. *International Journal of Advanced Robotic Systems*, 14(6), 2017.

[120] Yuanhui Zhang. *Indoor air quality engineering.* CRC press Boca Raton, FL, 2005.

[121] Achim Lilienthal, Holger Ulmer, HAAS Frohlich, A Stutzle, Felix Werner, and Andreas Zell. Gas source declaration with a mobile robot. In *Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference on*, volume 2, pages 1430–1435. IEEE, 2004.

[122] Achim J Lilienthal, Tom Duckett, Hiroshi Ishida, and Felix Werner. Indicators of gas source proximity using metal oxide sensors in a turbulent environment. In *Biomedical Robotics and Biomechatronics, 2006. BioRob 2006. The First IEEE/RAS-EMBS International Conference on*, pages 733–738. IEEE, 2006.

[123] Adam T Hayes, Alcherio Martinoli, and Rodney M Goodman. Distributed odor source localization. *IEEE Sensors Journal*, 2(3):260–271, 2002.

[124] Jean Vertut. *Teleoperation and robotics: applications and technology*, volume 3. Springer Science & Business Media, 2013.

[125] Keiji Nagatani, Seiga Kiribayashi, Yoshito Okada, Kazuki Otake, Kazuya Yoshida, Satoshi Tadokoro, Takeshi Nishimura, Tomoaki Yoshida, Eiji Koyanagi, Mineo Fukushima, et al. Emergency response to the nuclear accident at the fukushima daiichi nuclear power plants using mobile rescue robots. *Journal of Field Robotics*, 30(1):44–63, 2013.

[126] Gordon M Mair. Telepresence-the technology and its economic and social implications. In *Technology and Society, 1997.'Technology and Society at A Time of Sweeping Change'. Proceedings., 1997 International Symposium on*, pages 118–124. IEEE, 1997.

[127] Matteo Reggente and Achim J Lilienthal. Using local wind information for gas distribution mapping in outdoor environments with a mobile robot. In *SENSORS, 2009 IEEE*, pages 1715–1720. IEEE, 2009.

[128] Tomoya Yamada, Satoshi Yokoyama, Tomohiro Tanikawa, Koichi Hirota, and Michitaka Hirose. Wearable olfactory display: Using odor in outdoor environment. In *null*, pages 199–206. IEEE, 2006.

[129] Fumitaka Nakaizumi, Haruo Noma, Kenichi Hosaka, and Yasuyuki Yanagida. Spotscents: A novel method of natural scent delivery using multiple scent projectors. In *Virtual Reality Conference, 2006*, pages 207–214. IEEE, 2006.

[130] David Warnock, Marilyn McGee-Lennon, and Stephen Brewster. The role of modality in notification performance. In *IFIP Conference on Human-Computer Interaction*, pages 572–588. Springer, 2011.

[131] Takamichi Nakamoto and Hai Pham Dinh Minh. Improvement of olfactory display using solenoid valves. In *Virtual Reality Conference, 2007. VR'07. IEEE*, pages 179–186. IEEE, 2007.

[132] Gordon M Mair. Towards transparent telepresence. In *International Conference on Virtual Reality*, pages 300–309. Springer, 2007.

[133] RM Hainer, AG Emslie, and Ada Jacobson. An information theory of olfaction. *Annals of the New York Academy of Sciences*, 58(1):158–174, 1954.

[134] Valerie A Thompson, Jamie A Prowse Turner, and Gordon Pennycook. Intuition, reason, and metacognition. *Cognitive psychology*, 63(3):107–140, 2011.

[135] Danielle S Bassett, Nicholas F Wymbs, Mason A Porter, Peter J Mucha, Jean M Carlson, and Scott T Grafton. Dynamic reconfiguration of human brain networks during learning. *Proceedings of the National Academy of Sciences*, 2011.

[136] RC Miall and JK Jackson. Adaptation to visual feedback delays in manual tracking: evidence against the smith predictor model of human visually guided action. *Experimental Brain Research*, 172(1):77–84, 2006.

[137] Mike Oaksford and Nick Chater. *Bayesian rationality: The probabilistic approach to human reasoning.* Oxford University Press, 2007.

[138] Jose-Raul Ruiz-Sarmiento, Cipriano Galindo, and Javier Gonzalez-Jimenez. Building multiversal semantic maps for mobile robot operation. *Knowledge-Based Systems*, 119:257–272, 2017.

[139] Wijnand IJsselsteijn. Telepresence: Transforming transparency. *Dutch Electronic Arts Festival (DEAF '04), The Art of Immersive Spaces*, pages 29–31, 2004.

[140] C-Y Chow. An introduction to computational fluid mechanics. *New York, John Wiley and Sons, Inc., 1979. 408 p.*, 1979.

[141] John David Anderson and J Wendt. *Computational fluid dynamics*, volume 206. Springer, 1995.

[142] Dominique Thévenin and Gábor Janiga. *Optimization and computational fluid dynamics.* Springer Science & Business Media, 2008.

[143] Achim J Lilienthal, Matteo Reggente, Marco Trincavelli, Jose Luis Blanco, and Javier Gonzalez. A statistical approach to gas distribution modelling with mobile robots-the kernel dm+ v algorithm. In *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 570–576. IEEE, 2009.

[144] Andrew Keats, Eugene Yee, and Fue-Sang Lien. Bayesian inference for source determination with applications to a complex urban environment. *Atmospheric environment*, 41(3):465–479, 2007.

[145] S Pal Arya et al. *Air pollution meteorology and dispersion*, volume 6. Oxford University Press New York, 1999.

[146] James EA John. *Gas dynamics.* Allyn and Bacon Inc., Newton, MA, 1984.

[147] Javier Monroy, Mariano Jaimez, and Javier Gonzalez-Jimenez. Online estimation of 2d wind maps for olfactory robots. In *International Symposium on Olfaction and Electronic Nose (ISOEN)*, pages 1–3, 2017.

[148] Wataru Tsujita, Akihito Yoshino, Hiroshi Ishida, and Toyosaka Moriizumi. Gas sensor network for air-pollution monitoring. *Sensors and Actuators B: Chemical*, 110(2):304–311, 2005.

[149] Ali Marjovi, Adrian Arfire, and Alcherio Martinoli. High resolution air pollution maps in urban environments using mobile sensor networks. In *2015 International Conference on Distributed Computing in Sensor Systems*, pages 11–20. IEEE, 2015.

[150] Mirbek Turduev, Yunus Ataş, Pedro Sousa, Veysel Gazi, and Lino Marques. Cooperative chemical concentration map building using decentralized asynchronous particle swarm optimization based search by mobile robots. In *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4175–4180. IEEE, 2010.

[151] Ali Marjovi and Lino Marques. Multi-robot odor distribution mapping in realistic time-variant conditions. In *2014 IEEE Int. Conference on Robotics and Automation (ICRA)*, pages 3720–3727. IEEE, 2014.

[152] Marcos Portabella Arnús. *Wind field retrieval from satellite radar systems*. Universitat de Barcelona, 2002.

[153] Paula Doubrawa, Rebecca J. Barthelmie, Sara C. Pryor, Charlotte B. Hasager, Merete Badger, and Ioanna Karagali. Satellite winds as a tool for offshore wind resource assessment: The great lakes wind atlas. *Remote Sensing of Environment*, 168:349 – 359, 2015.

[154] Lars Landberg, Lisbeth Myllerup, Ole Rathmann, Erik Lundtang Petersen, Bo Hoffmann Jørgensen, Jake Badger, and Niels Gylling Mortensen. Wind resource estimation—an overview. *Wind Energy: An International Journal for Progress and Applications in Wind Power Conversion Technology*, 6(3):261–271, 2003.

[155] Georg A Grell, Jimy Dudhia, and David R Stauffer. A description of the fifth-generation penn state/ncar mesoscale model (mm5). ncar technical note. *National Center for Atmospheric Research, Boulder*, 1994.

[156] René Laprise, Daniel Caya, Guy Bergeron, and Michel Giguère. The formulation of the andré robert mc2 (mesoscale compressible community) model. *Atmosphere-Ocean*, 35(sup1):195–220, 1997.

[157] Shinsuke Kato and Shuzo Murakami. New ventilation efficiency scales based on spatial distribution of contaminant concentration aided by numerical simulation. *American Society of Heating, Refrigerating and Air-conditioning Engineers (ASHRAE) Transactions*, pages 09–330, 1988.

[158] Gideon Kowadlo and R. Andrew Russell. Improving the robustness of naïve physics airflow mapping, using bayesian reasoning on a multiple hypothesis tree. *Robotics and Autonomous Systems*, 57(6-7):723 – 737, 2009.

[159] Leopoldo Rodriguez, Jose A Cobano, and Anibal Ollero. Wind field estimation and identification having shear wind and discrete gusts features with a small uas. In *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 5638–5644. IEEE, 2016.

[160] Victor Hernandez Bennetts, Tomasz Piotr Kucner, Erik Schaffernicht, Patrick P. Neumann, Han Fan, and Achim J. Lilienthal. Probabilistic air flow modelling using turbulent and laminar characteristics for ground and aerial robots. *IEEE Robotics and Automation Letters*, 2017.

[161] José-Luis Blanco, Javier Monroy, Javier Gonzalez-Jimenez, and Achim Lilienthal. A kalman filter based approach to probabilistic gas distribution mapping. In *Proceedings of the 28th Annual ACM Symposium on Applied Computing*, pages 217–222, 2013.

[162] Javier Monroy and Javier Gonzalez-Jimenez. Towards odor-sensitive mobile robots. In *Rapid Automation: Concepts, Methodologies, Tools, and Applications*, pages 1491–1510. IGI Global, 2019.

[163] Cyrill Stachniss, Christian Plagemann, and Achim J Lilienthal. Learning gas distribution models using sparse gaussian process mixtures. *Autonomous Robots*, 26(2-3):187–202, 2009.

[164] Ji-Gong Li, Biao Sun, Fan-Lin Zeng, Jia Liu, Jing Yang, and Li Yang. Experimental study on multiple odor sources mapping by a mobile robot in time-varying airflow environment. In *2016 35th Chinese Control Conference (CCC)*, pages 6032–6037. IEEE, 2016.

[165] David Portugal and Rui P Rocha. Extracting topological information from grid maps for robot navigation. In *ICAART (1)*, pages 137–143, 2012.

[166] Peter Clifford. Markov random fields in statistics. *Disorder in physical systems: A volume in honour of John M. Hammersley*, 19, 1990.

[167] Nasser M Nasrabadi. Pattern recognition and machine learning. *Journal of electronic imaging*, 16(4):049901, 2007.

[168] Joseph Katz and Allen Plotkin. *Low-speed aerodynamics*, volume 13. Cambridge university press, 2001.

[169] Deborah A Kaminski and Michael K Jensen. *Introduction to thermal and fluids engineering*. Wiley New York, 2005.

[170] James M Hyman and Mikhail Shashkov. Natural discretizations for the divergence, gradient, and curl on logically rectangular grids. *Computers & Mathematics with Applications*, 33(4):81–104, 1997.

[171] Robert N Meroney. Wind-tunnel experiments on dense gas dispersion. *Journal of hazardous materials*, 6(1-2):85–106, 1982.

[172] Fotini K Chow, Patrick W Granvold, and Curtis M Oldenburg. Modeling the effects of topography and wind on atmospheric dispersion of co2 surface leakage at geologic carbon sequestration sites. *Energy Procedia*, 1(1):1925–1932, 2009.

[173] DK Heist, SG Perry, and LA Brixey. A wind tunnel study of the effect of roadway configurations on the dispersion of traffic-related pollution. *Atmospheric Environment*, 43(32):5101–5111, 2009.

[174] Hrvoje Jasak, Aleksandar Jemcov, Zeljko Tukovic, et al. Openfoam: A C++ library for complex physics simulations. In *International workshop on coupled methods in numerical dynamics*, volume 1000, pages 1–20. IUC Dubrovnik Croatia, 2007.

[175] Kaj Madsen, Hans Bruun Nielsen, and Ole Tingleff. Methods for non-linear least squares problems, 1999.

[176] Juan-Antonio Fernández-Madrigal. *Simultaneous Localization and Mapping for Mobile Robots: Introduction and Methods: Introduction and Methods*. IGI global, 2012.

[177] John E Dennis Jr and Robert B Schnabel. *Numerical methods for unconstrained optimization and nonlinear equations*, volume 16. Siam, 1996.

[178] Yudi Pawitan. *In all likelihood: statistical modelling and inference using likelihood*. Oxford University Press, 2001.

[179] David Eigen and Rob Fergus. Predicting depth, surface normals and semantic labels with a common multi-scale convolutional architecture. In *Proceedings of the IEEE int. conf. on computer vision*, pages 2650–2658, 2015.

[180] L James Lo, David Banks, and Atila Novoselac. Combined wind tunnel and cfd analysis for indoor airflow prediction of wind-driven cross ventilation. *Building and environment*, 60:12–23, 2013.

[181] Jose-Luis Blanco, Javier González-Jiménez, and Juan-Antonio Fernández-Madrigal. An alternative to the mahalanobis distance for determining optimal correspondences in data association. *IEEE transactions on robotics*, 28(4):980–986, 2012.

[182] Henry G Weller, Gavin Tabor, Hrvoje Jasak, and Christer Fureby. A tensorial approach to computational continuum mechanics using object-oriented techniques. *Computers in physics*, 12(6):620–631, 1998.

[183] Jay A Farrell, John Murlis, Xuezhu Long, Wei Li, and Ring T Cardé. Filament-based atmospheric dispersion model to achieve short time-scale structure of odor plumes. *Environmental fluid mechanics*, 2(1-2):143–169, 2002.

[184] Matteo Luperto, Javier Monroy, Francisco-Angel Moreno, J. R. Ruiz-Sarmiento, Nicola Basilico, Javier Gonzalez-Jimenez, and N. Alberto Borghese. A multi-actor framework centered around an assististe mobile robot for elderly people living alone. In *IEEE International Conference on Intelligent Robots - Workshop on Robots for Assisted Living (IROS)*, 2018.

[185] Andres Gongora, Javier Monroy, and Javier Gonzalez-Jimenez. An electronic architecture for multipurpose artificial noses. *Journal of Sensors*, 2018, 2018.

[186] Javier G Monroy, Javier González-Jiménez, and Jose Luis Blanco. Overcoming the slow recovery of mox gas sensors through a system modeling approach. *Sensors*, 12(10):13664–13680, 2012.

[187] Mariano Jaimez, Javier Monroy, Manuel Lopez-Antequera, and Javier Gonzalez-Jimenez. Robust planar odometry based on symmetric range flow and multi-scan alignment. *IEEE Trans. on Robotics*, pages 1623–1635, 2018.

[188] Young-Duk Kim, Yoon-Gu Kim, Seung-Hyun Lee, Jeong-Ho Kang, and Jinung An. Portable fire evacuation guide robot system. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 2789–2794, 2009.

[189] Paul Robinette, Patricio A Vela, and Ayanna M Howard. Information propagation applied to robot-assisted evacuation. In *IEEE International Conference on Robotics and Automation*, pages 856–861, 2012.

[190] Carlos Sánchez-Garrido, Javier Monroy, and Javier Gonzalez-Jimenez. Probabilistic estimation of the gas source location in indoor environments by combining gas and wind observations. In *Frontiers in Artificial Intelligence and Applications (FAIA), IOS Press*, pages 110–121. IOS Press, 2018.

[191] Aleksandar Rodic, Dusko Katie, and Gyula Mester. Ambient intelligent robot-sensor networks for environmental surveillance and remote sensing. In *IEEE 7th International Symposium on Intelligent Systems and Informatics*, pages 39–44, 2009.

[192] Andres Gongora, Alberto Jaenal, David Chaves, Javier Monroy, and Javier Gonzalez-Jimenez. Urban monitoring of unpleasant odors with a handheld electronic nose. In *ISOCS/IEEE International Symposium on Olfaction and Electronic Nose (ISOEN)*, pages 1–3, 2019.

[193] Michael Hutchinson, Hyondong Oh, and Wen-Hua Chen. A review of source term estimation methods for atmospheric dispersion events using static or mobile sensors. *Information Fusion*, 36:130–148, 2017.

[194] Amit Shukla and Hamad Karki. Application of robotics in onshore oil and gas industry—a review part i. *Robotics and Autonomous Systems*, 75:490–507, 2016.

[195] Karl Johan Åström. Optimal control of Markov processes with incomplete state information. *Journal of Mathematical Analysis and Applications*, 10(1):174–205, 1965.

[196] Sebastian Thrun. Probabilistic robotics. *Communications of the ACM*, 45(3):52–57, 2002.

[197] B Lorena Villarreal, Gustavo Olague, and José Luis Gordillo. Synthesis of odor tracking algorithms with genetic programming. *Neurocomputing*, 175:1019–1032, 2016.

[198] Christos H Papadimitriou and John N Tsitsiklis. The complexity of markov decision processes. *Mathematics of Operations Research*, 12(3):441–450, 1987.

[199] Mikko Lauri and Risto Ritala. Planning for robotic exploration based on forward simulation. *Robotics and Autonomous Systems*, 83:15–31, 2016.

[200] Solomon Kullback and Richard A Leibler. On information and sufficiency. *The annals of mathematical statistics*, 22(1):79–86, 1951.

[201]

[202] Thomas Lochmatter. *Bio-inspired and probabilistic algorithms for distributed odor source localization using mobile robots*. PhD thesis, PhD Thesis No. 4628, EPFL, 2010, 2010.

[203] Thomas Lochmatter, Pierre Roduit, Chris Cianci, Nikolaus Correll, Jacques Jacot, and Alcherio Martinoli. SwisTrack - A flexible open source tracking software for multi-agent systems. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4004–4010, 2008.

[204] Morgan Quigley, Ken Conley, Brian Gerkey, Josh Faust, Tully Foote, Jeremy Leibs, Rob Wheeler, and Andrew Y Ng. ROS: an open-source Robot Operating System. In *ICRA workshop on open source software*, number 3.2, page 5. Kobe, Japan, 2009.

[205] Andres Gongora and Javier Gonzalez-Jimenez. Olfactory telerobotics. a feasible solution for teleoperated localization of gas sources? *Robotics and Autonomous Systems*, 113:1 – 9, 2019.

[206] Carlos Sánchez-Garrido, Javier Gonzalez Monroy, and Javier González Jiménez. Probabilistic estimation of the gas source location in indoor environments by combining gas and wind observations. In *APPIS*, pages 110–121, 2018.

[207] Frank Lees. *Lees' Loss prevention in the process industries: Hazard identification, assessment and control.* Butterworth-Heinemann, 2012.

[208] Silvano Dragonieri, Marc P van der Schee, Tommaso Massaro, Nunzia Schiavulli, Paul Brinkman, Armando Pinca, Pierluigi Carratú, Antonio Spanevello, Onofrio Resta, Marina Musti, et al. An electronic nose distinguishes exhaled breath of patients with malignant pleural mesothelioma from controls. *Lung Cancer*, 75(3):326–331, 2012.

[209] James M Lents and Patricia Leyden. Reclaim: Los angeles' new market-based smog cleanup program. *Journal of the Air & Waste Management Association*, 46(3):195–206, 1996.

[210] Rob W Holland, Merel Hendriks, and Henk Aarts. Smells like clean spirit: Nonconscious effects of scent on cognition and behavior. *Psychological Science*, 16(9):689–693, 2005.

[211] Daniele Quercia, Rossano Schifanella, Luca Maria Aiello, and Kate McLean. Smelly maps: the digital life of urban smellscapes. *arXiv preprint arXiv:1505.06851*, 2015.

[212] Tracey P Lauriault and Gitte Lindgaard. Scented cybercartography: exploring possibilities. *Cartographica: The Int. Journal for Geographic Information and Geovisualization*, 41(1):73–92, 2006.

[213] Sharvari Deshmukh, Rajib Bandyopadhyay, Nabarun Bhattacharyya, RA Pandey, and Arun Jana. Application of electronic nose for industrial odors and gaseous emissions measurement and monitoring–an overview. *Talanta*, 144:329–340, 2015.

[214] Zaher Al Barakeh, Philippe Breuil, Nathalie Redon, Christophe Pijolat, Nadine Locoge, and Jean-Paul Viricelle. Development of a normalized multi-sensors system for low cost on-line atmospheric pollution detection. *Sensors and Actuators B: Chemical*, 241:1235–1243, 2017.

[215] Brett J Doleman and Nathan S Lewis. Comparison of odor detection thresholds and odor discriminablities of a conducting polymer composite electronic nose versus mammalian olfaction. *Sensors and Actuators B: Chemical*, 72(1):41–50, 2001.

[216] Lei Fang, Geo Clausen, and Povl Ole Fanger. Impact of temperature and humidity on the perception of indoor air quality. *Indoor air*, 8(2):80–90, 1998.

[217] Daniele Quercia, Luca Maria Aiello, Rossano Schifanella, et al. The emotional and chromatic layers of urban smells. In *ICWSM*, pages 309–318, 2016.

[218] Piotr S Gromski, Elon Correa, Andrew A Vaughan, David C Wedge, Michael L Turner, and Royston Goodacre. A comparison of different chemometrics approaches for the robust classification of electronic nose data. *Analytical and bioanalytical chemistry*, 406(29):7581–7590, 2014.

[219] Philip L Hanst, Ngai Woon Wong, and Joseph Bragin. A long-path infra-red study of los angeles smog. *Atmospheric Environment (1967)*, 16(5):969–981, 1982.

[220] Sylvain Delplanque, Didier Grandjean, Christelle Chrea, Laurence Aymard, Isabelle Cayeux, Bénédicte Le Calvé, Maria Inés Velazco, Klaus R. Scherer, and David Sander. Emotional processing of odors: Evidence for a nonlinear relation between pleasantness and familiarity evaluations. *Chemical Senses*, 33(5):469–479, 2008.

[221] RP Arasaradnam, CU Nwokolo, KD Bardhan, and JA Covington. Electronic nose versus canine nose: clash of the titans. *Gut*, pages gut–2011, 2011.

[222] Yukie Hirata. A study of the effective way to release scent to maintain alertness. *JSAE review*, 22(3):331–336, 2001.

[223] Lidia Eusebio, Laura Capelli, and Selena Sironi. Electronic nose testing procedure for the definition of minimum performance requirements for environmental odor monitoring. *Sensors*, 16(9):1548, 2016.

[224] Manuel Aleixandre, Enrique Montero, Teresa Arroyo, Juan Mariano Cabellos, and María Carmen Horrillo. Quantitative analysis of wine mixtures using an electronic olfactory system. In *Multidisciplinary Digital Publishing Institute Proceedings*, volume 1, page 450, 2017.

[225] S Ampuero and JO Bosset. The electronic nose applied to dairy products: a review. *Sensors and Actuators B: Chemical*, 94(1):1–12, 2003.

[226] A Guadarrama, ML Rodrıguez-Méndez, C Sanz, JL Rıos, and JA De Saja. Electronic nose based on conducting polymers for the quality control of the olive oil aroma: discrimination of quality, variety of olive and geographic origin. *Analytica Chimica Acta*, 432(2):283–292, 2001.

[227] Jia Yan, Xiuzhen Guo, Shukai Duan, Pengfei Jia, Lidan Wang, Chao Peng, and Songlin Zhang. Electronic nose feature extraction methods: A review. *Sensors*, 15(11):27804–27831, 2015.

[228] Ricardo Gutierrez-Osuna, H Troy Nagle, and Susan S Schiffman. Transient response analysis of an electronic nose using multi-exponential models. *Sensors and Actuators B: Chemical*, 61:170–182, 1999.

[229] Laurent Ratton, Tekin Kunt, Thomas McAvoy, Thomas Fuja, Richard Cavicchi, and Steve Semancik. A comparative study of signal processing techniques for clustering microsensor data (a first step towards an artificial nose). *Sensors and Actuators B: Chemical*, 41(1-3):105–120, 1997.

[230] Sylvie Roussel, Gustaf Forsberg, Vincent Steinmetz, Pierre Grenier, and Véronique Bellon-Maurel. Optimisation of electronic nose measurements. part i: Methodology of output feature selection. *Journal of food engineering*, 37(2):207–222, 1998.

[231] Yann LeCun, Yoshua Bengio, et al. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, 3361(10):1995, 1995.

[232] Ron Kohavi et al. A study of cross-validation and bootstrap for accuracy estimation and model selection. In *IJCAI*, volume 14, pages 1137–1145. Montreal, Canada, 1995.

[233] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, Nov 1998.

[234] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. Imagenet classification with deep convolutional neural networks. In *Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1*, NIPS'12, pages 1097–1105, USA, 2012. Curran Associates Inc.

[235] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.

[236] Unease because of a strong fuel-like smell in a neighbourhood of coria del río [news article in Spanish] Inquietud por un fuerte olor a gasoil en la barriada Guadalquivir de Coria del Río. *ABCdesevilla*, 18th September 2017.

[237] The Regional Ministry of the Environment and Territorial Organization of Andalusia will analyze the air quality in coria del río after an episode

of strong odors [news article in Spanish] Medio Ambiente analizará la calidad del aire en Coria del Río por un episodio de fuertes olores. *Noticias de la Junta de Andalucia*, 23th September 2017.

[238] The sewer contamination in a town of Sevilla causes the neighbours health problems. [news article in Spanish] La contaminación del alcantarillado de un pueblo de Sevilla genera problemas de salud a los vecinos. *El Diario*, 23th September 2017.

[239] Eftade O Gaga, Tuncay Döğeroğlu, Özlem Özden, Akif Ari, Ozan Devrim Yay, Hicran Altuğ, Nesimi Akyol, Sermin Örnektekin, and Wim Van Doorn. Evaluation of air quality by passive and active sampling in an urban city in turkey: current status and spatial analysis of air pollution exposure. *Environmental Science and Pollution Research*, 19(8):3579–3596, 2012.

[240] Latests investigations are very close to finding the origin of coria's gases. [news article in Spanish] Las investigaciones, muy cerca de hallar el origen de los gases de Coria. *ABCdesevilla*, 31th July 2018.