

Review

Chemical Detection Using Mobile Platforms and AI-Based Data Processing Technologies

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Abstract: The development of reliable gas sensors is very important in many fields such as safety, environment, and agriculture, and is especially essential for industrial waste and air pollution monitoring. As the performance of mobile platforms equipped with sensors such as smartphones and drones and the technologies supporting them (wireless communication, battery performance, data processing technology, etc.) are spreading and improving, a lot of efforts are being made to perform these tasks by using portable systems such as smartphones or installing them on unmanned wireless platforms such as drones. For example, research is continuously being conducted on chemical sensors for field monitoring using smartphones and rapid monitoring of air pollution using unmanned aerial vehicles (UAVs). In this paper, we review the measurement results of various chemical sensors available on mobile platforms including drones and smartphones, and the analysis of detection results using machine learning. This topic covers a wide range of specialized fields such as materials engineering, aerospace engineering, physics, chemistry, environmental engineering, electrical engineering, and machine learning, and it is difficult for experts in one field to grasp the entire content. Therefore, we have explained various concepts with relatively simple pictures so that experts in various fields can comprehensively understand the overall topics.

Keywords: chemical sensor; optical detection; electrochemical; drone; unmanned aerial vehicles; mobile platform



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1. Introduction

The development of reliable gas sensors is very important in many fields such as public safety, medical applications, agriculture, and especially monitoring industrial waste and air pollution. With the help of mobile platforms such as unmanned aerial vehicles (UAVs) and the development of wireless communications, rapid air pollution monitoring has become possible [1,2]. In addition, the continuous development of AI or data processing algorithms may enable the rapid determination of gas molecule types and concentrations in the near future. However, the spatial mapping of gas concentrations in the atmosphere and localization of gas leaks utilizing chemical sensing technologies on various mobile platforms still remain a challenging task.

Depending on the sensing mechanism, chemical sensing methods include resistive-type, electrochemical, and optical methods. Mobile platforms equipped with these sensors come in various types such as drones, handheld portable devices, and chip-type micro

sensors that can be connected to smartphones. Thanks to the improvements in the sensitivity and selectivity of chemical sensors together with the development of materials such as plasmonic nanomaterials as well as artificial intelligence (AI)-based data processing, there have been enormous developments in chemical detection using wireless unmanned mobile platforms.

There have been various studies and reviews on chemical substances and pollutant detection using mobile platforms such as smartphones, robots, and drones [3–8]. However, reviews on the advantages and disadvantages and applicability according to the characteristics of the platform and sensors are somewhat limited. In this paper, we reviewed the results of various chemical detections available on mobile platforms including drones and smartphones, and the analysis of the sensing results utilizing machine learning. We try to provide a comprehensive understanding of applicable technologies and their characteristics according to mobile platforms. This topic covers a very wide range of specialized fields such as material science, aeronautical engineering, physics, chemistry, environmental engineering, electronics, and machine learning, and it is difficult for experts in one field to grasp the overall content. Thus, we illustrate relatively simple concepts with figures and pictures to help experts in various fields understand the overall concepts comprehensively.

In Section 2, we present an overview of chemical detection using various mobile platforms in order to introduce general concepts and the importance of chemical detection with various mobile platforms. In Section 3, we discuss the gas sensing mechanisms of various chemical sensors together with their basic structures, and in Section 4, we review chemical detection results using optical and other sensing methods, focusing on drone applications including the effect of UAV structures and the influence of airflow near the UAV. Then, in Section 5, we discuss the environmental impacts (temperature, humidity, flow rate, etc.) of the chemical sensors for drone applications. Finally, in Section 6, we discuss AI-based data processing techniques using chemical detection results.

2. Overview of Chemical Detection Using Mobile Platforms

This section briefly describes the main applications used for chemical sensors on drones and smartphones, etc. For UAV applications, non-dispersive infrared (NDIR) sensors that use the infrared absorption of molecules have been most commonly used; meanwhile, for smartphone applications, colorimetric and electrochemical sensors are frequently used. Figure 1 illustrates the types of mobile platforms and sensing methods that can be adopted for mobile platforms. In this review, we will discuss mobile platforms including UAVs, robots, smartphones, portable devices, and satellites adapting Infrared (IR) absorption-based detectors (such as NDIR detectors illustrated in Figure 2), chemiresistor sensors, electrochemical sensors, fluorescence sensors, colorimetric sensors, and hyperspectral cameras. More detailed descriptions of resistive-type, electrochemical, and optical sensors are given in the next section.

Mobile Platform	Sensing Method
UAV	IR absorption based sensor
	Chemoresistive sensor
Robot	Electrochemical sensor
	Fluorescence sensor
Smart phone, Portable device	Colorimetric sensor
	Hyperspectral camera
Satellite	

Figure 1. Mobile platforms and sensing methods.

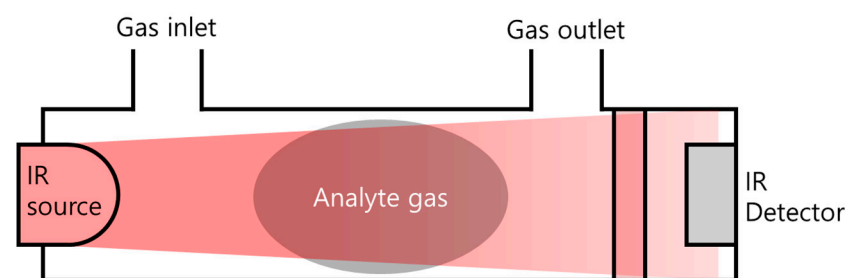


Figure 2. A schematic diagram of an NDIR detector.

2.1. Chemical Detection Using Drones

There is growing interest in equipping drones with gas sensors, as they can provide long-term, continuous monitoring of sources of hazardous gas emissions in industrial areas. They also have the advantage of being able to observe areas that are geographically difficult for humans to access, such as landfills, wastewater treatment plants [9,10], military border areas, and areas with frequent volcanic eruptions. Although various gas sensors can be mounted on drones, the chemical sensors which are most commonly utilized on UAVs are infrared sensors that use a laser of a specific infrared wavelength to detect the concentration of molecules by absorption of light at the wavelength (Figure 2) [9,11,12].

UAVs equipped with gas sensors can provide data on atmospheric greenhouse gas components (e.g., CH_4 , CO_2) in the lower troposphere. These measurements are much less expensive than manned aircraft, can scan larger areas of space than fixed monitoring methods, and can provide better spatial resolution than satellite-based measurements [13]. In the NDIR method, absorption by specific molecules can be measured immediately when air is drawn into the chamber through an air intake either built-in on the drone or a pylon mounted on the base of a drone, making it relatively easy to obtain gas concentration mapping. Figure 3 shows examples of gases and volatile organic compounds (VOCs) that need to be monitored. The emission sources are explained together.

If the spatial distribution of gas concentrations can be obtained using drones, this is useful for air quality monitoring in urban areas and for assessing the diffusion of target gases after fires, chemical leaks and accidents, and volcanic eruptions [14–19]. To construct a gas distribution map, a drone typically follows a predefined navigation path with equidistant measurement points to measure gas concentrations.

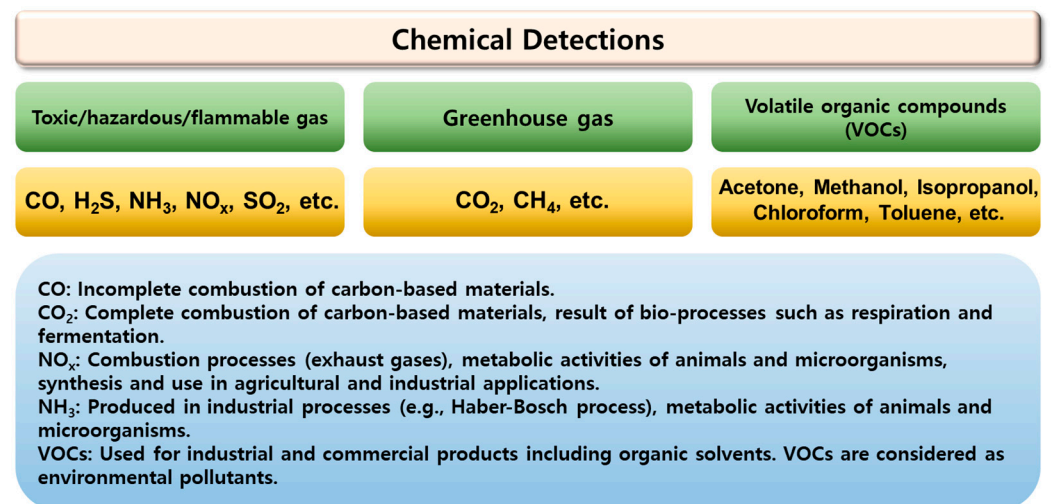


Figure 3. Examples of gases and VOCs that need to be monitored or detected. The emission sources are explained together.

Figure 4 shows chemical detection in an open field using UAVs. The target gases and detection methods are methane using backscattered-tunable diode laser absorption spectroscopy (TDLAS), CO₂ using an NDIR detector, odorous gases using an electronic nose (e-nose) composed of electrochemical, NDIR, and metal oxide semiconductor (MOS) sensors, respectively.

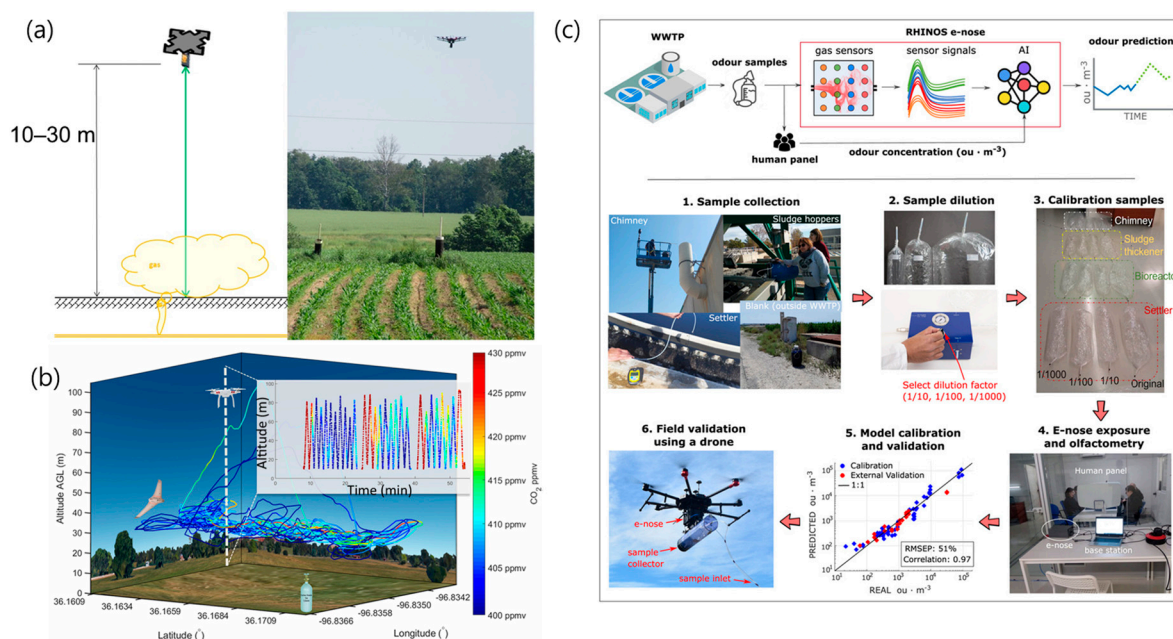


Figure 4. Examples of chemical detection using drones. (a) Detection of methane leakage using backscattered-tunable diode laser absorption spectroscopy (Backscattered-TDLAS) [11]. Copyright 2021 by Iwaszenko et al. Reprinted with permission. (b) Response of NDIR CO₂ detector during the flight of small unmanned aerial systems (quadcopter for vertical profiles and fixed-wing for horizontal profiles) with programmed gas release [12]. Copyright 2019 by Schuyler et al. Reprinted with permission. (c) Odor prediction process using e-nose adopted on a UAV [9]. Copyright 2021 by Elsevier. Reprinted with permission.

In optical measurements, spectrometers are often used in a laboratory. If a spectrometer was used for drones, optical alignment issues might occur during the operation. Thus, instead of using a spectrometer, either an optical bandpass filter with a specific wavelength

or a hyperspectral camera may be utilized. In a fluorescence method, light-emitting diodes can be used as excitation light, and only optical filters appropriate for the fluorescence wavelength can be used without a spectrometer, which has the advantage of application to mobile platforms. Since the fluorescence method is sensitive to the detection of explosive molecules, research on this topic is being conducted in South Korea to utilize robots or drones. In the fluorescence method, airflow is very important for sensitivity [20,21].

Resistive or chemiresistive sensors are typically inexpensive, but when a drone flies to an area where the concentration of molecules changes rapidly, there is a typical delay of several seconds to tens of seconds depending on the time it takes for molecules to be desorbed since the sensors utilize the change in resistance caused by gas molecules adsorbed to the sensing material (oxide semiconductor). The situation is somewhat similar for the fluorescence method, but the response is typically somewhat slower in resistive sensors. Therefore, a strategy to obtain the spatial distribution of gas concentrations or to localize the gas source is necessary [1,2]. For example, a drone can be paused for several seconds to measure the gas concentration or can change its flying direction. Regarding this issue, the NDIR method seems to be the most superior for obtaining the spatial distribution of gas concentration using drones, although only one type of molecule can be detected at once since the IR absorption at a specific wavelength is associated with the molecular vibration energy.

Another challenge with resistive or electrochemical sensors is associated with the variations in the temperature and humidity when a drone flies over a wide area. For resistive-type sensors, the resistance of a sensing material is sensitive to the change in humidity, even when the temperature of the sensor is fixed at around 300 C. For example, Schuyler et al. used inexpensive chemical sensors to correct the results for the effect of temperature at different relative humidity [12]. Also, the electrochemical current and fluorescence intensity can be fairly sensitive to the temperatures. On the other hand, when using a drone, the sensor output changes quickly over time as it passes through an area where the concentration of the molecule being sensed increases, so it is relatively less affected by the long-term drift of the sensor, which is a great advantage.

Over the past two decades, small drones have been used to capture vertical and horizontal profiles of atmospheric greenhouse gases and ozone in the atmospheric boundary layer. Watai et al. used a drone equipped with an NDIR sensor to probe CO₂ changes up to 2000 m in height, and NDIR sensors mounted on drones have been used to measure surface fluxes in CO₂. Several authors have exploited the ability of drones to fly horizontally and vertically to probe vertical and horizontal changes in atmospheric greenhouse gases [1,22].

With the advancement of autonomous driving technology, robots equipped with sensors can be used to detect hazardous gases or explosives in hazardous areas such as minefields. Fluorescence quenching and GPR are widely used for explosive detection.

Figure 5a shows landmine detection methods including optical imaging (surface landmines), metal detector (landmines including metal components), fluorescence methods (detection of specific explosives), ion mass mobility spectroscopy (analysis of specific explosive signals from the spectrum), GPR (imaging of buried objects), and X-ray (imaging of buried objects). Among the methods, the optical imaging using a visible or infrared camera is one of the cost-efficient techniques. Figure 5b shows a proposed system architecture for optical imaging and mapping of surface landmines [23]. The images obtained from these kinds of systems can be processed with AI technologies. The images in the right box of Figure 5b show examples of object detection using a neural network model. For buried landmines, GPR is one of the predominant techniques. Figure 5c,d show a GPR system adopted on a robotic platform (Figure 5c [24]) and on a UAV (Figure 5d [25]).

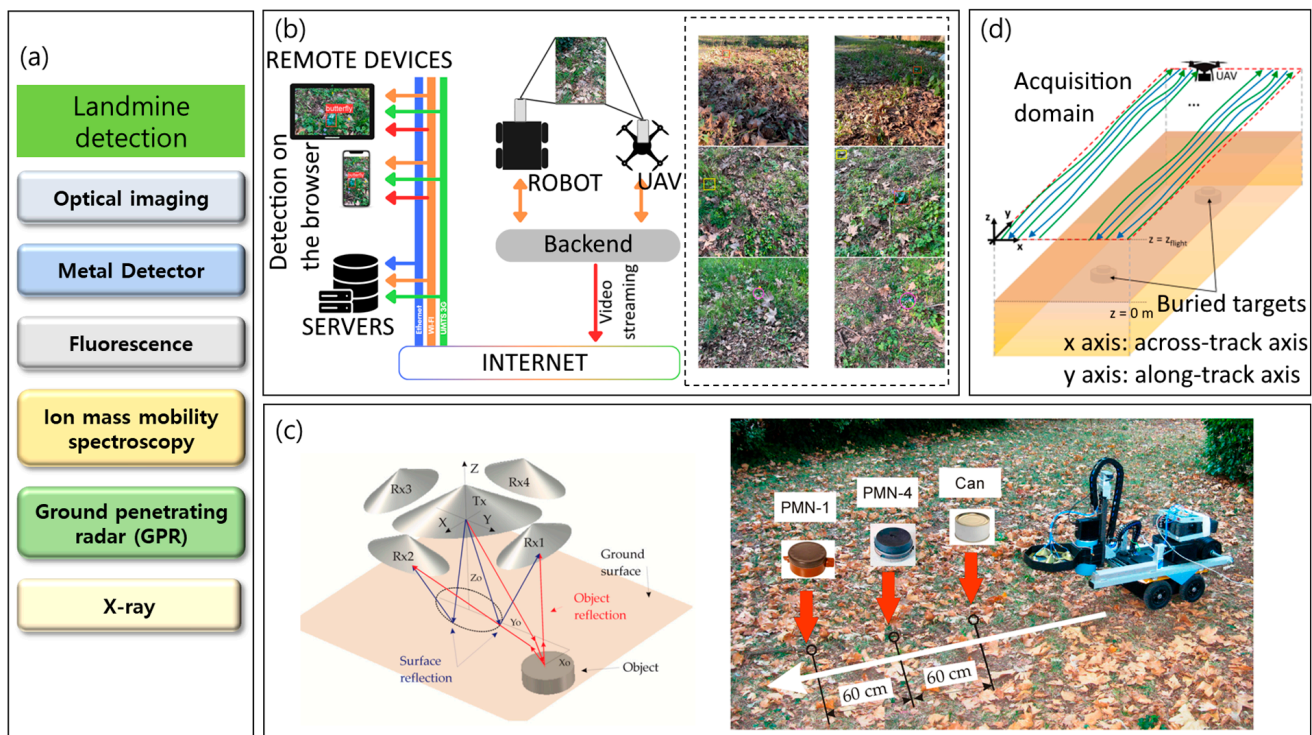


Figure 5. (a) Detection techniques for landmines. (b) The system architecture proposed for surface landmine detection (left) and object detection results of “starfish” (left 3 images) and “butterfly” (right 3 images) landmines. The red rectangles, yellow rectangles, and purple circles indicate correct, wrong, and missing object detection results in the images on the right box [23]. Copyright 2024 by Vivoli et al. (c) Schematic illustration of the ground penetrating radar (GPR) configured with the 1Tx + 4Rx antenna system (left). A photograph of the robotic platform on the linear test path is also shown (right) [24]. Copyright 2022 by Pryshchenko et al. (d) Illustration of the flight path for airborne-based GPR system [25]. Copyright 2022 by García-Fernández et al. Reprinted with permission.

Sato et al. presented a handheld detector with a GPR and a metal detector, and airborne-based GPR-SAR imaging has been realized for landmine and IED detection systems [25–31]. They found that the L and S bands (1–4 GHz) offer a good trade-off between penetration depth and image resolution (free-space down-range resolution is around 5–7 cm). Robots are generally slower than UAVs but can carry larger payloads and have fewer restrictions on power consumption.

2.2. Miniaturized Sensors for Smartphones and Portable Detectors

In addition to platforms that can drive autonomously or by remote control such as UAVs and robots, many studies are being conducted on smartphone-mounted sensors and portable detectors. Figure 6 shows the chemical sensor applications using a smartphone. One of the approaches for adapting chemical sensors for a smartphone was the development of an extra module including chemical sensors such as electrochemical sensors. Figure 7a,b show extra electrochemical modules communicating with a smartphone using near-field communication (NFC) wireless communication and USB communication [32,33]. In addition, portable sensing modules that can communicate data with smartphones using wireless communication such as Bluetooth, WiFi, and NFC have already been developed, and commercial products that can perform electrochemical measurements with additional accessories to smartphones are available.

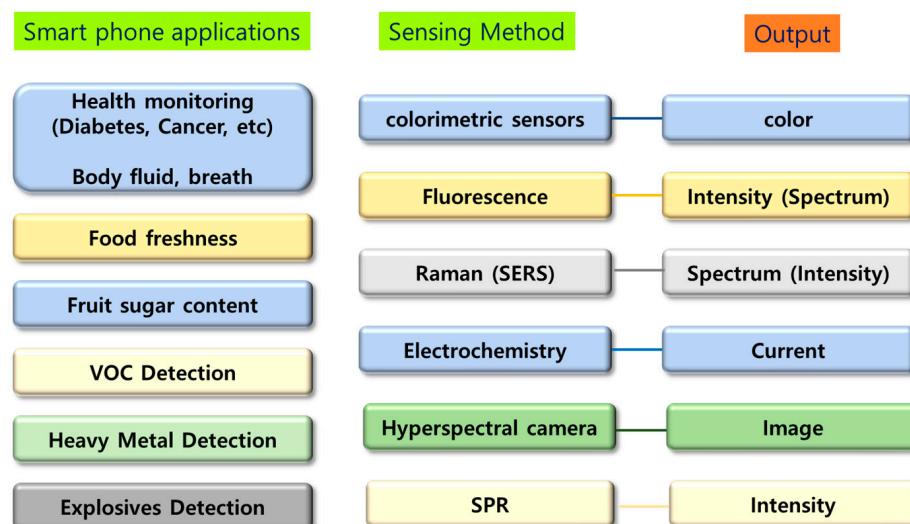


Figure 6. Applications of smartphone chemical sensors and the sensing methods.

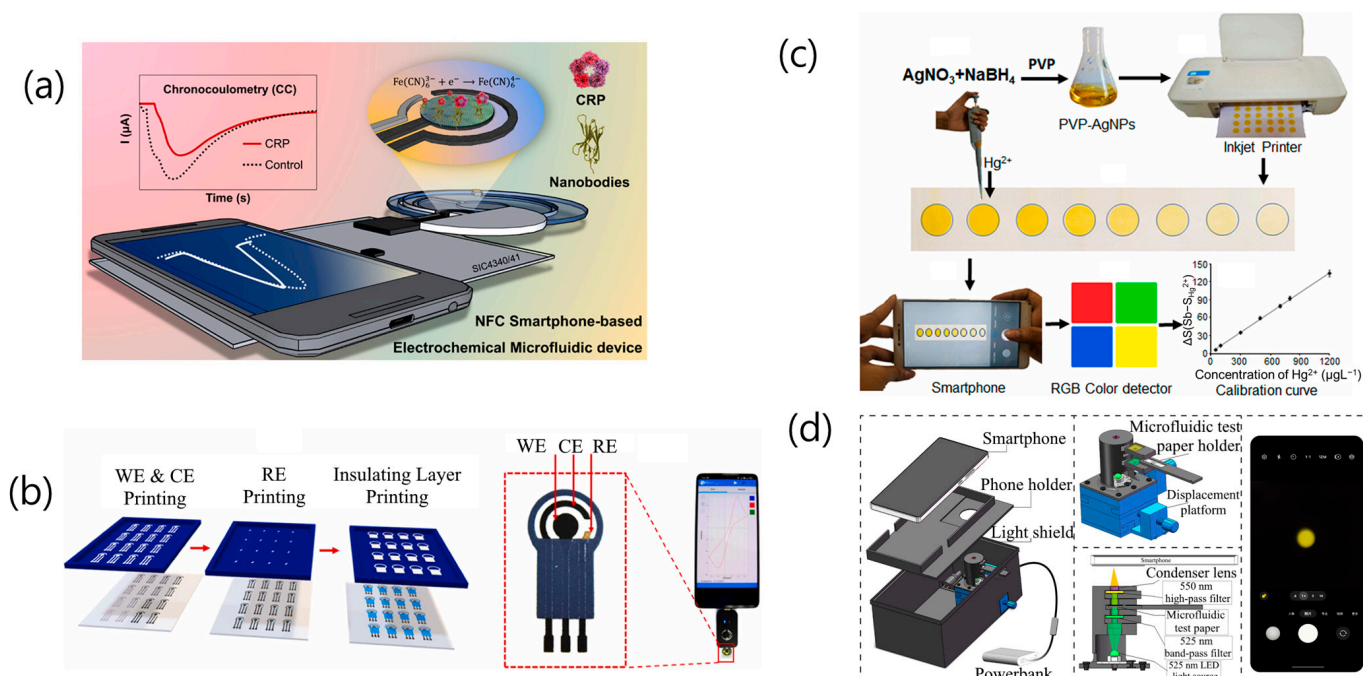


Figure 7. (a) Wireless communication module for electrochemical detection [32]. Copyright 2024 by Boonkaew et al. (b) Additional electrochemical module adapted for a smartphone [33]. Copyright 2021 by Elsevier. Reprinted with permission. (c) Inkjet-printed colorimetric chemical sensor with optical analysis using a smartphone [34]. Copyright 2021 by Elsevier. Reprinted with permission. (d) Microfluidic paper-based fluorometric chemical sensor with optical analysis using a smartphone and attachment [35]. Copyright 2024 by Elsevier. Reprinted with permission.

One of the most widely studied and applied methods in sensing applications using smartphones is optical sensing such as a colorimetric sensor using smartphone cameras. The performance of camera modules and data processors in smartphones has been continuously improving, making it possible to perform optical measurements utilizing smartphones without using complex and expensive optical systems. In particular, improvements in the color resolution and spatial resolution of smartphone cameras can contribute to improved color accuracy and spectral resolution in colorimetric sensing. In addition, data analysis is expected to become easier when combined with machine vision and machine learning technologies that have been actively developed recently.

Sensing techniques that can utilize the camera of a smartphone include a colorimetric sensor, fluorometric sensor, surface-enhanced Raman spectroscopy, and surface-plasmon resonance. Figure 7c,d show colorimetric and fluorometric sensors using a smartphone camera [34,35]. In this section, we mainly focus on colorimetric sensors [36].

The simplest and most representative example of a colorimetric sensor is a method of detecting a color change through a chemical reaction, such as litmus paper for checking pH. In the case of test strips commonly used for urine tests in hospital examinations, paper coated with reagents for measuring glucose, protein, pH, etc. (e.g., glucose oxidase enzyme for detecting glucose) is attached to a plastic strip, and the presence and concentration of each component can be roughly confirmed based on the color after the reaction.

Colorimetric sensors are usually designed for single use and are often discarded after testing due to hygiene issues and the difficulty of reusing the sensor. For example, the urine test strips mentioned above are not reversible and are not suitable for repeated use due to the risk of contamination, and thus they are discarded after one use. These single-use designs have the advantage of simplicity and practicality, but it may be difficult for users to calibrate by themselves; the test strips are often calibrated during the production process and then delivered to customers. However, if more accurate measurements are required, additional calibration can be performed, such as compensating for the effects of ambient light or comparing with a standard sample or blank sample.

In the case of colorimetric sensors, since color and the degree of change must be confirmed together, a table is usually referred to when visually checking. However, such visual confirmation can be somewhat inaccurate, and especially in the case of concentration measurement, the color changes that can be identified with the naked eye are limited, and there may be differences depending on the individual, so there are studies that have attempted to measure this easily and accurately with a smartphone.

Although image sensors enable more accurate measurements, data storage, and transfer than the naked eye, there are still challenges to overcome. In a paper written by Fan et al., they reviewed engineering solutions to problems such as inaccurate color information depending on lighting conditions in point-of-care diagnostics using smartphones, adapter standardization, and repeatability problems depending on smartphone models, data preprocessing and postprocessing (white balancing, etc.), and differences in spectral sensitivity depending on cameras [36]. We will discuss data processing for fluorescence and colorimetric sensors using machine learning in Section 6.4.

Portable devices such as COVID-19 disease test devices that utilize immunochromatography techniques are widely used in daily life, and they are similar to colorimetric sensors in that they display test results in color. This technique performs a test by utilizing the reaction between antigens or antibodies contained in body fluids, etc., and antibodies/antigens prepared in a test kit. Antigens or antibodies are sometimes conjugated with materials that exhibit inert properties and can display colors, such as gold nanoparticles [37]. These tests often display the test results in the form of colored lines, and while they allow for easy and fast testing and intuitive result analysis, they have the limitation that they can only test for the presence or absence of specific antigens/antibodies.

There have also been efforts to develop colorimetric sensors that can detect a wider range of chemicals. For example, Zhang et al. prepared probe molecules using naphthalene as a material to detect F^- , CN^- , and nitroaromatic explosives, and evaluated their selectivity and sensitivity for each target in fluorimetric and colorimetric methods [38]. In the case of F^- and CN^- , the color changed from transparent to pink and yellow, respectively, upon mixing with the probe molecule in solution, and in the case of trinitrotoluene (TNT) and trinitrophenol (TNP), the solution color changed to deep red and yellow, respectively.

2.3. Hyperspectral Cameras on Satellites

Hyperspectral cameras capable of observing greenhouse gases such as methane and carbon dioxide have been developed and are being installed on satellites. While CCD cameras obtain red, green, and blue (RGB) color information, hyperspectral imaging often uses detectors capable of measuring longer wavelengths in the IR region, allowing for additional information such as the type of material in the terrain or the temperature distribution. The principles of hyperspectral imaging are explained in the next section.

3. Gas Sensing Mechanisms and Device Structures

3.1. Optical Methods

In addition to the infrared absorption method described earlier (Figure 2), optical methods also include colorimetric sensors, fluorescence (or photoluminescence) sensors in which the fluorescence signal of a thin film is weakened by chemical molecules [20,21], surface plasmon resonance that detects the change in refractive index in the presence of chemicals on the surface of a prism, and surface-enhanced Raman scattering (SERS) methods that detect the Raman spectrum in which the signals of well-defined vibrational modes of the molecules are enhanced by surface plasmon effects [39].

Optical methods include fine dust sensors utilizing light scattering, infra-red thermal imaging cameras that detect heat generation from defective electrical equipment components, and hyperspectral imaging cameras that can capture hundreds of narrow spectral bands to measure the reflectance of various features (factory buildings, fields, grass, etc.), or to measure the absorption of light in the atmosphere.

The operating principle of the NDIR sensor is that gas molecules such as CO₂ or NO₂ absorb specific IR wavelengths corresponding to their molecular vibrational modes. The system consists of an infrared (IR) lamp, a sample chamber through which air passes, and an IR detector to measure the reduced intensity. Since a lamp has a relatively broad wavelength band, an optical filter that only passes the specific wavelength can be used. The decrease in intensity due to the gas molecules is proportional to the concentration of the gas in the sample chamber. Unlike resistive or electrochemical sensors that detect changes due to the adsorption of molecules, the response time is independent of the time taken for the adsorption/desorption of molecules to the sensing materials. Therefore, the absorption changes immediately according to the change in gas concentration. This fast response and recovery time make it very suitable for drones. Figure 8a shows various optical (infrared) gas sensor topologies including the NDIR detector set-up [40].

The IR absorption method also has a great advantage in that the absorption is relatively less affected by the temperature and humidity of the environment in contrast to both the resistance type sensors and electrochemical sensors. The electrochemical current changes with temperature due to a thermodynamic influence. Also, for resistance-type sensors, there is a resistance change depending on the moisture in the air. When these sensors are mounted on a fast-moving object such as a drone, the output value may be rapidly affected by the humidity and temperature of the outside air in the flying area.

To further improve the environmental impacts, NDIR often uses sophisticated components such as temperature and pressure compensation systems, which increase power consumption; however, without such compensation, power consumption is only a few mW. NDIR sensors are generally larger and heavier than resistive or electrochemical sensors, but with the development of IR light-emitting diode (LED) light sources with low power consumption, they are widely used in drones [41].

The strong optical absorption and low cross-sensitivity (narrow absorption band without overlap) of CO₂ at 4.26 μm (in the MIR range) allow for sensitive (ppb-level L.O.D.)

and selective detection of CO₂. In contrast, other gases, such as O₃, have non-overlapping spectral regions in the near-UV range.

In the case of CH₄, Shi et al. demonstrated excellent linear responses of the fabricated sensor in the range of 1000–30,000 ppm CH₄ and stability of the sensor to humidity. In addition, by using a filter (3.295 μm) corresponding to the absorption wavelength of CH₄, the signal interference caused by other gases (CO (4.66 μm) and CO₂ (4.26 μm)) was reduced and the selectivity for CH₄ was increased [42]. However, the absorption at about 3.3 μm overlaps with the absorption of H₂O, and compensation may be necessary [1,40,42–44].

Unlike NDIR, tunable diode laser absorption spectroscopy (TDLAS) uses a frequency-modulated tunable diode laser as its light source. It can operate via a closed-path or an open-air path cell; with the closed-path design using a multi-pass cell with temperature and pressure compensation to achieve better quality measurements, the system has slower response times due to the time required to fill the gas cell. A portable TDLAS measurement set-up and the CO₂ and H₂O measurement results are shown in Figure 8b [45]. Open-path instruments are less accurate but lighter and faster. The compact open path tunable diode laser methane sensor developed by NASA for the Mars Curiosity rover has been adapted for use on drones. The open-path laser spectrometer is reported to be very light, fast, and sensitive (10 ppb), and has been reported to detect methane plumes 200 m downwind from the source [46].

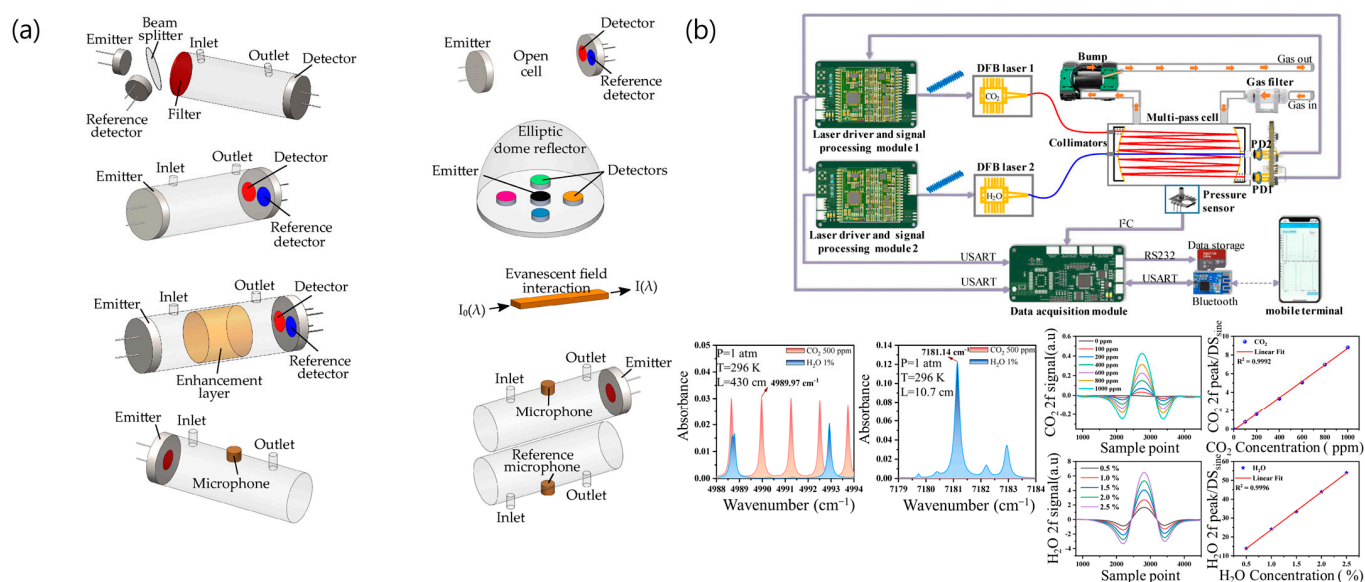


Figure 8. (a) Infrared gas sensor topologies [40]. Copyright 2019 by Popa et al. (b) A TDLAS measurement set-up and CO₂ and H₂O measurement results [45]. Copyright 2023 by Gu et al.

Another option for mobile and portable applications is remote detection technologies. The remote detection of targets in the gas phase includes advantages such as ease of access to measurement areas, as well as the potential for imaging gas distribution at the target area. However, since the measurements are usually performed via IR absorption spectroscopy, the gas concentration can be obtained with integrated absorption through the optical path in a concentration $\times$ distance dimension (e.g., ppm·m unit). One of the widely used IR-based remote detection applications is the remote methane leak detector (RMLD). Figure 9a shows a photograph of a remote methane leak detector (RMLD)-adapted UAV (left) and a drawing of the remote gas detection mechanism (right) [47]. Many commercialized RMLD detectors are handheld TDLAS systems that measure backscattered IR laser light and the absorption through the optical path. Figure 9b shows the simulation results and the experimental set-up and results with the optical system, which is a combination of TDLAS

and optical ranging technologies [48]. The combination of TDLAS and optical ranging technologies (in this case, time-of-flight measurement) can provide spatially resolved absorption and scattering information, which can be utilized for particle-laden flow. The spatially distributed particles can produce time-resolved scattering and reflection of IR light, which appear as relatively broad spectral features compared to narrower absorption spectral features.

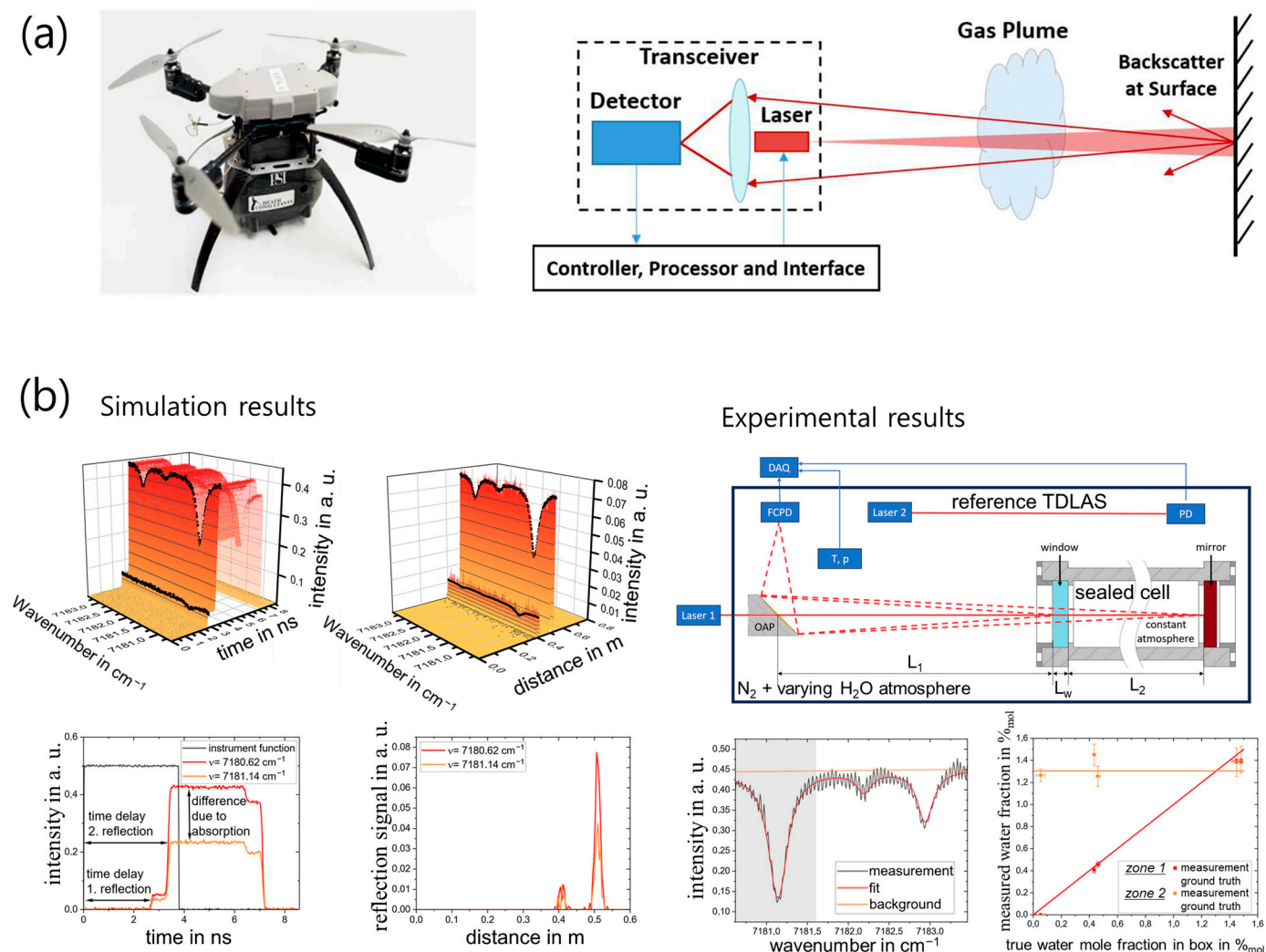


Figure 9. (a) A photograph of a remote methane leak detector (RMLD)-adapted UAV (left) and a drawing of the remote gas detection mechanism (right) [47]. Copyright 2018 by Yang et al. (b) Simulation (left) and experimental (right) results of single-ended TDLAS measurement. The experimental set-up is also shown together [48]. Copyright 2024 by Hansemann et al.

The dust sensors utilize the scattering of light by fine dust particles (Figure 10a). It is similar to NDIR in that it has a light source and a detector, but rather than using the absorption of molecules, it measures the change in scattering due to the fine dust particles to analyze the concentration and size of the particles.

Most fluorescence sensors utilize the change in fluorescence intensity of conjugated polymers by chemical molecules. Thus, an excitation light source, an optical filter, a photodiode, and a fluorescent substance that reacts with gas molecules are required for the fluorescence system. When electrons are excited and lose energy by emitting light, it is called luminescence, and if the excitation method is by light, it is called photoluminescence. Therefore, the excitation wavelength must be shorter than the fluorescence wavelength. The term fluorescence is commonly used in the fields of atomic and molecular physics and

polymers. The term photoluminescence can be used regardless of the material, but here, as in most polymer papers, the term fluorescence is used.

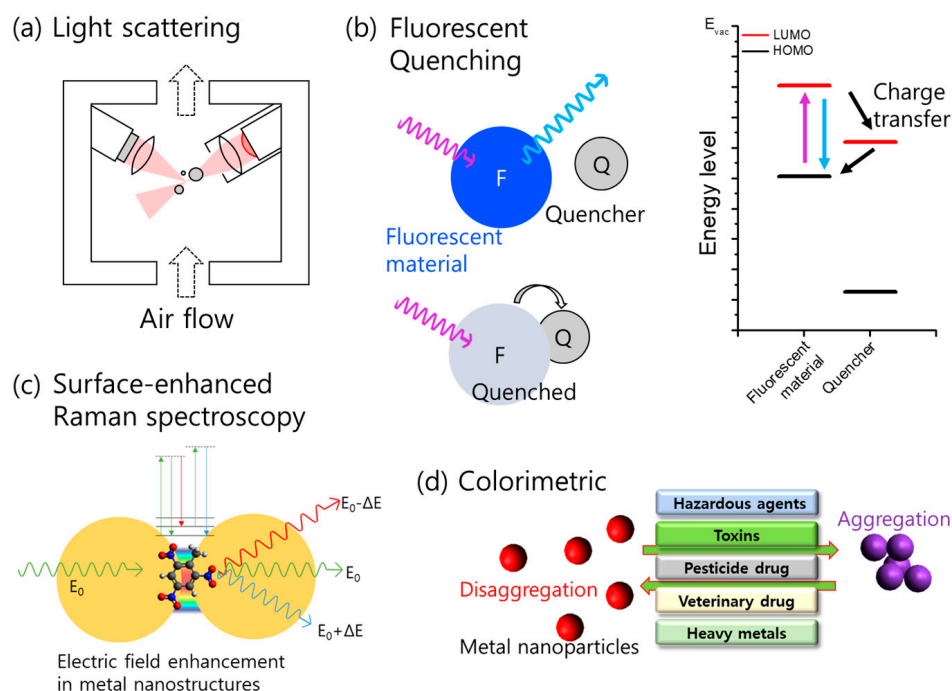


Figure 10. Optical technologies for chemical detection. (a) Dust detector. (b) Fluorescence quenching-based chemical detection technology. (c) Surface-enhanced Raman spectroscopy. (d) Metal nanoparticle aggregation-based colorimetric sensing technology.

Fluorescence sensing is most frequently used for liquid-phase detection that senses contaminants in a solution. For gas-phase detection, a fluorescent polymer film is installed in a passage through which air passes, and changes in fluorescence intensity are detected when contaminant molecules in the air are adsorbed on the film.

To apply the fluorescence method to a drone, sufficient airflow is required [20]. The air intake into the air passage can be achieved using a fan or air pump, and the air passage can be built into the drone or located on a pylon mounted on the base of the drone, similar to the NDIR method. The main reason for the decrease in fluorescence intensity is known to be that the electrons transfer from the lowest unoccupied molecular orbital (LUMO) level of the conjugated polymer to the LUMO level of the molecule. (Figure 10b). This is called electron transfer, and for electron transfer, the LUMO energy of the conjugated polymer must be sufficiently high. Not only lasers but also LEDs (light-emitting diodes) can be used as the excitation light source, and if an optical filter appropriate for the fluorescence wavelength is used without a spectrometer, there are no problems with payload, power consumption, and optical alignment, and this method can be applied to drones.

Since the fluorescence quenching rate is correlated with factors such as molecular structure, electrical binding strength, types of fluorophore–quencher interactions, etc., the fluorescent sensing material can be designed to have a certain degree of selectivity [49,50].

Instead of conjugation polymers, quantum dots and metal nanoparticles can be used, and multiple contaminants can be detected by using nanomaterials with different fluorescence wavelengths [51,52]. Not only the presence or absence of contaminants but also quantitative analysis is possible. In addition, since the light source and CCD of a smartphone can be utilized, it is also being applied to smartphones. Section 6.4 explains such examples.

Many explosive materials, such as TNT or dinitrotoluene (DNT), contain nitro groups (NO_2) which are known to be electron acceptors, and it is known that some conjugated polymers exhibit efficient fluorescence quenching in sensing nitroaromatic molecules. Research on fluorescence-based explosive detection using robots and UAVs is actively under progress in South Korea.

SERS utilizes Raman scattering, where photons from an incident light source interact with molecules and slightly change their wavelengths. Raman shift is the difference between the energy of the incident photon (hf) and the energy of the scattered photon (hf'), which corresponds to the vibrational energy of the molecules. Since the value of the Raman shift is typically small, it is necessary to differentiate Raman signals whose energies are very close to the incident photon energy of the incident light. Thus, it is difficult to detect Raman signals using an LED light source with a broad band, and a laser is used for excitation light.

Raman signals are typically much weaker than fluorescence, and a SERS substrate that can amplify the intensity by a factor larger than 10^8 can be utilized [39,53,54]. The SERS substrate is made of a metal nanostructure such as gold or silver nanogaps (Figure 10c), and SERS utilizes surface plasmon, where the electric field near the metal surface is amplified by the long interaction of the incident laser light with the metal surface. A SERS device requires a laser as a light source, a spectrometer, a SERS substrate, and a photodiode.

Raman equipment is typically large and expensive, but recently a handheld Raman apparatus using a spectrometer the size of a fingernail has become available. SERS substrates can generally oxidize in the air after long-term use, and once contaminant molecules stick to them, they tend to adhere to them, making recovery time longer than a few minutes [39]. Most SERS substrates need to be vacuum packed for long-time storage before use, and in the case of liquid-phase detection, plasma treatment is sometimes necessary to improve the surface state of the substrates from hydrophobicity to hydrophilicity. In many cases, the intensity from SERS is still weaker than that from the NDIR method, which uses the absorption of light corresponding to vibrational energy.

When using a smartphone for SERS, a CCD can be used instead of a separate photodiode, and if a hyperspectral camera is used instead of a CCD, SERS spectra can be obtained without a spectrometer. In addition to well-known chemicals such as ethanol, SERS can detect pesticides, explosives, microplastics, etc., and its great advantages are excellent selectivity and sensitivity [39,53–55]. However, depending on the type of target materials, the SERS signal may be small, and in the case of viruses and bacteria, it is difficult to expect a surface enhancement effect in metal nano-gaps due to their large size. In such cases, one may use nanoprobe materials or instead measure the signal of a reporter material that can generate a Raman signal [56,57].

Recently, technologies are being developed to determine the presence of analytes in Raman signals from contaminants in agricultural products or foods through machine learning signal processing, or to determine multiple analytes from complex Raman signals. SERS can be mounted on a smartphone as an accessory, through which the Raman signal from the SERS substrate is sent to the smartphone [58].

Colorimetric response sensors use the principle that color changes depending on the presence of contaminants, allowing the presence of the contaminants to be immediately identified with the naked eye. Portable colorimetric sensors illuminate a sample using an LED light source. RGB intensity is read from the reflected light, and converted to a standard color space, allowing accurate color representation and relative comparison [59–61]. Photo-based image analysis software can be used for the quantitative analysis of color changes. Smartphone-based methods offer portable convenience, making them easily accessible to both medical professionals and the general public. Integration with smartphone

technology also enables data sharing, remote monitoring, and integration with cloud-based databases [62–64]. The paper-based nature of the test strips allows for inexpensive manufacturing, making them ideal for mass production.

Colorimetric sensors can utilize a variety of reactions, but the most common method involves fixing receptors that can recognize contaminants to precious metal nanoparticles such as gold or silver, and cause color to change through particle aggregation or redox reactions when contaminants are captured on the nanoparticles [65]; the contaminants can be qualitatively or quantitatively analyzed by detecting color changes or by using changes in the surface plasmon wavelength of metal nanoparticles.

The principle of color change due to oxidation–reduction reactions on the surface of nanoparticles can be used to detect heavy metals [34,66]. In addition, colorimetric sensors can detect not only relatively small pesticide residues, insecticides, and nitro explosive molecules, but also bacteria measuring several microns [67]. Smartphone colorimetric sensors can be used for medical diagnosis (diabetes, cancer, etc.) using body fluids such as saliva or sweat, environmental monitoring (water quality assessment, etc.), and food safety (pesticide residues, insecticides, etc.) [33,65–67].

Hyperspectral imaging is a technique for measuring optical spectra from camera pixels. Hyperspectral imaging can provide additional information such as material or temperature distribution by combining visible and IR data and by obtaining more spectral data compared to conventional RGB images. In the fabrication process of camera pixels, the Fabry–Perot type resonance structure is utilized to adjust the thickness of the multilayer to suit the resonance of various wavelengths other than RGB. Depending on the type of hyperspectral camera, the number of spectral bands may range from tens to thousands, and the spectral resolution can be tens of nm to several nm or less. In hyperspectral sensors, an image stack representing the intensity of the corresponding band (wavelength interval) is acquired and provided. Hyperspectral imaging is also called hyperspectral data cube because the spectra are added to imaging in this way. The first two dimensions are spatial dimensions and the third dimension is a spectral dimension, which are vectors containing reflectance spectra or reflectance values. Hyperspectral imaging is being actively studied for various applications such as measuring the freshness of fruits, diagnosing skin conditions, and testing water quality. There are many research and review papers on data processing of hyperspectral imaging [68].

3.2. Resistive Sensors

Resistance-type chemical sensors use the change in resistance of a material when a pollutant is adsorbed. A representative material for a resistance type sensor is a MOS such as SnO_2 . When an analyte molecule is adsorbed on the surface, the thickness of the depletion layer on the semiconductor surface changes due to the movement of charge (i.e., redox process), resulting in resistance changes (Figure 11a). Resistive sensors typically require high operating temperatures, typically above 200 °C, to overcome the activation energy barrier for changing the resistivity. The structure of the sensor consists of electrodes for measuring the resistance and a heater connected to the bottom of the sensing material to maintain high operating temperatures. Figure 11b shows a micro-electromechanical system (MEMS) device including electrodes and heater. The bottom shows the IR radiation images [69].

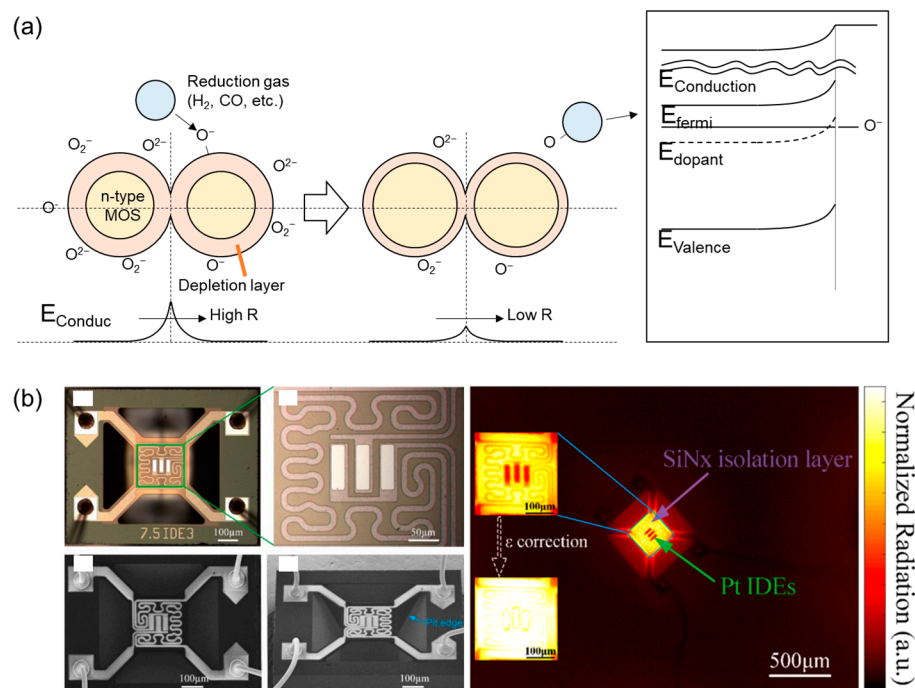


Figure 11. (a) A schematic drawing of the working mechanism for a n-type MOS gas sensor. (b) Images of MEMS device and the thermographic camera image [69]. Copyright 2021 by Chen et al.

Many studies have been conducted on resistive sensors for the purpose of detecting toxic gases such as NO_2 and NH_3 , or VOCs such as benzene and toluene. Gas molecules with similar redox properties can be difficult to distinguish from each other in sensor responses, and various attempts were made to improve selectivity [70]. The most popular ones are the use of multivariate predictive models that take into account the response of the entire sensor array [71], exploiting the dynamic response due to sampling transients or temperature modulation [72,73], functionalization of MOS surfaces [70,74–77], and doping of MOS [78–80]. Jeong et al. compared NiO gas sensors with different material geometry and dopant types [81–86]. Graphene has promising prospects in the field of gas sensors with ultrahigh sensitivity, but its selectivity is not satisfactory [87,88].

Since the exchange of charges between volatile substances and metal oxide films, or the redox process governs the sensing mechanism, there are several drawbacks in the resistive type sensors [89,90], including the reaction drift (degradation), the impacts of environmental factors such as humidity and temperature, and a relatively slow reaction rate [91,92].

3.3. Electrochemical Sensors

The electrochemical method is somewhat similar to the resistive method, but it measures the redox current resulting from the exchange of electrons between the working electrode and the target molecules. Electrochemistry is basically the energy conversion between chemical energy and electrical energy. Thus, the electrochemical current between the working electrode and the counter electrode is measured while controlling the electrical potential applied to the electrodes (Figure 12a). When the Fermi level of the working electrode is higher than the reduction energy level (E_{red}), electrons come out of the working electrode and reduction occurs, and conversely, if the Fermi level of the working electrode is lower than the oxidation energy, electrons move to the working electrode.

For gas sensing applications, hydrophobic diffusion membranes are frequently used to enable the selective diffusion of target molecules into the electrolyte and to prevent the sensor from malfunctioning in the presence of moisture and contaminants. For the

liquid-phase detection, an analyte solution can be directly contacted with the electrodes. Screen-printed electrodes are widely used for liquid-phase detection because of the compact size and low cost. However, the pH and ion concentration can affect the base current level and sensor sensitivity. Figure 12b illustrates a typical electrochemical gas sensor structure and a screen-printed electrode design. Here, the electrochemical gas sensor includes solution-phase electrolytes such as aqueous H_2SO_4 , and it is necessary to prevent leakage and drying of the electrolyte. To overcome this, other types of electrolytes, such as gel-electrolytes, have been utilized [93,94]. Figure 12c shows the structure and photos of an electrochemical CO gas sensor using a gel-electrolyte [94].

The potential-current characteristics and the time-current characteristics can be obtained using various electrochemical measurement techniques such as cyclic voltammetry (CV), chronoamperometry (CA), differential pulsed voltammetry (DPV), and electrochemical impedance spectroscopy (EIS). Among these, CV and CA are frequently used techniques because the circuit configuration and signal processing are relatively simple.

The common target gases detected electrochemically include VOCs (e.g., acetone, methanol, ethanol, benzene, and toluene) and redox gases (e.g., O_3 , NO_2 , SO_2 , NO , H_2S , CO , H_2 , and NH_3). In contrast, liquid-phase analytes, such as glucose, heavy metal ions, and biological substances (e.g., urea, hormones, proteins), are typically measured using liquid samples.

The main challenges of electrochemical gas sensors are slow recovery time, temperature/humidity sensitivity, and drift of the response over time.

Since redox reactions occur when the reactant molecules and the electrode are close together, the surface state of the electrode sensitively affects these reactions. In addition, the adsorption and diffusion of analyte molecules to the electrode play important roles in determining the reaction rate. Therefore, sensitivity and selectivity can be improved by using catalysts, metal nanoparticles, functional 2D and nanomaterials (e.g., transition metal dichalcogenides (TMDCs), and graphene), and artificial or biological receptors (e.g., molecularly imprinted polymers, antibodies, and aptamers).

In medical diagnosis and biomolecular detection research including cancer, high affinity and selectivity are being achieved using antibodies and enzymes, and research is also actively being conducted using receptors such as single-stranded DNA, called aptamers. Aptamers are artificially synthesized oligonucleotides that use DNA sequences that can bind well to the target molecules. Aptamers are utilized to sense various environmental hormones, cancer cells, explosive molecules, etc., and apta-sensors are in demand in the biomedical field due to their extraordinary properties of high sensitivity, specificity, and reproducibility [95]. Figure 12d shows the sensing process of protein detection using an electrochemical aptamer sensor [96,97].

Electrochemical sensors are used in various biosensor fields, including agriculture and food, due to their advantages such as low operating power, relatively high sensitivity, and simplicity. In addition, electrochemical sensors are advantageous for the estimation of the analyte concentration because the signals have good linearity between the concentration of the analyte and the measured current. When applied to a microfluidic chip for liquid-phase detection, the sensor size can be minimized, measurements can be made even with small samples, and integration into portable devices is possible [32]. Electrochemical sensors utilizing smartphones are being developed rapidly for use in agricultural and food contamination analysis or freshness measurement. Jie Wu, Hong Liu, et al. reviewed electrochemical biosensors and their integration into portable and mobile devices [98].

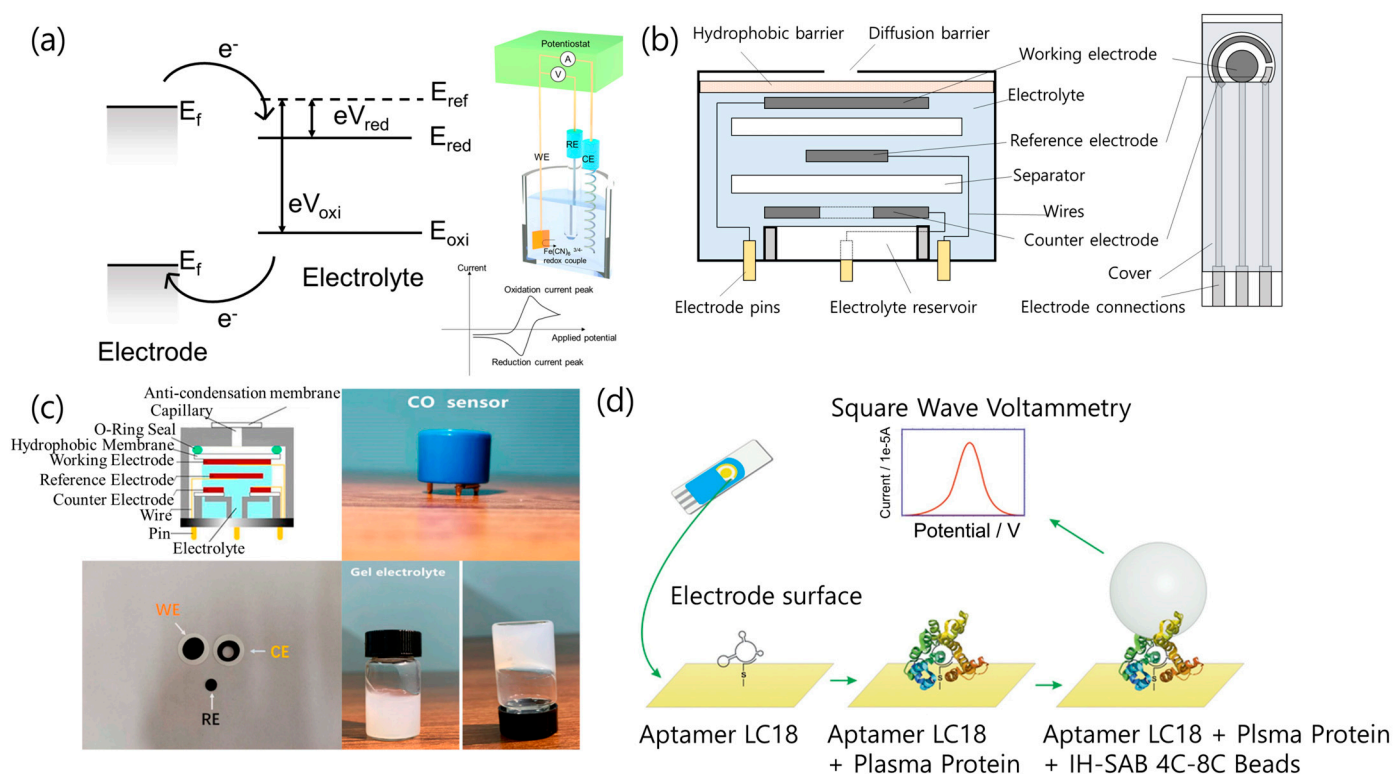


Figure 12. (a) Basic principle of an electrochemical measurement using $K_3Fe(CN)_6$ and $K_4Fe(CN)_6$ redox couple [96]. Copyright 2022 by Waifalkar et al. (b) A schematic drawing of an electrochemical gas sensor and a screen-printed electrode. (c) Device structure and photos of the electrochemical CO gas sensor using a gel-electrolyte [94]. Copyright 2020 by Zhang et al. (d) Detection process of a protein using an electrochemical aptamer sensor for cancer detection [97]. Copyright 2016 by Zamay et al.

4. Pollution Monitoring Using Drones

Although the NDIR sensor using IR absorption has a limited range of measurable molecule types compared to other methods because it utilizes the absorption of specific molecules, it has the advantages of being less sensitive to temperature and humidity, very fast in response, and high in selectivity, so it is most often used for detecting CO_2 and CH_4 in air pollution monitoring using UAVs. In this section, we discuss representative examples of chemical detection using drones, focusing on atmospheric air monitoring, gas leak detection, and VOC detection. Some applications using smartphones and portable devices will be discussed in Section 6.5 when we discuss the data processing for fluorescence and colorimetric methods.

The safety of the gas transmission infrastructure is one of the main concerns of infrastructure operators, and research has been actively conducted to detect pipeline natural gas leaks using UAVs equipped with NDIR for methane detection. The flying platform on the UAV's base may have built-in [11,47,99–101] or suspended methane detectors [102–104]. The system, consisting of backscatter tunable diode laser absorption spectroscopy equipment mounted on an autonomous UAV operating with localization algorithms, was field tested and used to detect and quantify natural gas leaks at controlled gas sources and real gas production facilities during blind tests [11,47,99]. Unlike NDIR, which uses absorption at a fixed wavelength, tunable diode laser absorption spectroscopy allows the detection of gases with close absorption wavelengths.

Several studies have conducted experiments on actual natural gas leaks from pipelines, using GPS coordinates to fly sensor-equipped UAVs directly over the gas pipeline route, after conducting adequate reconnaissance prior to flight to find terrain obstacles. The

measurement data were collected and analyzed using machine learning methods together with spatial coordinates, allowing the identification of spatial regions with increased methane concentrations. A study was also conducted on the influence of flight altitude on measurement accuracy, which showed that the lower the flight altitude, the better, with the optimal range being below 15 m [11].

Compared to chemiresistive or electrochemical sensors, optical sensors such as TDLAS exhibit a relatively fast response, and an optical response can be obtained while a drone flies at a constant speed. Tassielli et al. studied the effects of flying factors such as altitude and speed when measuring CH₄ gas concentration near the ground using a rotary-wing UAV equipped with a TDLAS sensor [105]. They placed CH₄ emission sources on the ground such as grass and concrete, and investigated the noise, background, and gas signals of the sensor while the UAV was moving at a specific speed. In grassy areas, the background signal increased due to the movement of the grass under strong wind, making it difficult to detect CH₄ accurately. On the other hand, in the suburban area, measurements were possible with relatively high precision; the estimated emission flux was 86% of the actual value. According to their measurements, the optimal conditions for detecting CH₄ gas using a TDLAS sensor attached to a rotary wing drone were a concrete floor (easier to interpret the reflected background signal compared to grass and less affected by wind), an altitude of 7~10 m (lowest background signal in their experimental conditions), a flight speed of 1~2 m/s (flight speed had relatively little effect), and a cloudy day with low wind speed (1.5~3 m/s).

In the near-surface measurements using TDLAS, airflow caused by the UAV can affect the sensor signal and the target gas concentration distribution. Marturano et al. studied the characteristics of the downstream by a UAV and the resulting sensor measurement fluctuations using Computational Fluid Dynamics (CFD) simulation [106]. According to the result, the drone's rotor created downwash air turbulence to a speed of 8~9 m/s at 2 m below the rotor, and the downwash reached 1~2 m/s at 25 m level below the drone. Thus, drones flying *at a sufficient velocity and height* over the target area may not generate downwash airflow that affect the gas concentration of specific target areas. Marturano et al. also discussed that the sensor positioning can affect the concentration measurement because the downward airflow caused by the rotor may hinder the gas molecules from moving into the sensor and suggested that a radial configuration of the sensors may be more advantageous than positioning the sensor at the center of the drone, based on a simulation for ammonia sensing.

Do et al. investigated the airflow near a UAV using particle image velocimetry (PIV) and performed dimethyl-methylphosphonate (DMMP) exposure experiments using carbon nanotube (CNT) capacitive sensors [107]. The PIV results demonstrated that the particle velocity was over 10 m/s under a rotor, and the vorticity of the airflow was high near the rotor. They confirmed that the measured sensor capacitance and response time varied depending on the sensor location; the location with the highest sensitivity and the fastest response was the middle of the UAV body, or a vortex-free area that is less affected by turbulence. This result is different from the results obtained by Marturano et al. However, this difference seems to be due to the differences in the size and structure of the drones used in the simulation and experiment, and it is already well known that the airflow distribution generated from the rotors can vary significantly depending on the design of the UAV [108].

In order to reduce the influence of airflow, several ideas have been proposed, such as connecting a hose or pipe to the sensor chamber to position the sampling inlet far from the UAV or separating the sensor platform from the UAV body [109]. However, some of these have limitations such as affecting the sensor performance or causing additional weight load

and power consumption. Therefore, it is important to select an appropriate UAV size and structure, sensor type and location, and flight strategy that suits the measurement purpose.

Emran, Tannant, and Najjaran proposed a UAV system to monitor CH₄ emissions from landfills and to map CH₄ concentrations, and Kamrat, Ostrowski, and Zastosowanie proposed a leak detection system for gas pipelines using fixed-wing UAVs and performed simulation tests of methane leaks along a programmed flight path. Tannant et al. performed field experiments using a UAV equipped with a laser methane mini-detector, presented maps showing higher methane concentrations above landfills, and also used the equipment to evaluate natural gas pipeline inspection.

Neumann et al. performed field experiments using a UAV equipped with sensors mounted on aerial gimbals suspended from an octocopter and reconstructed 2D distribution maps of gas plumes [110,111]. However, one must be aware of the potential for methane to originate from a variety of microbial sources of decomposing organic matter (e.g., rotting grass or other vegetation) or from landfills [11]. This can be achieved by first measuring the background of the study area and then by using a flying platform to further measure CH₄ concentrations at locations where the content is increased.

Most air pollution applications require monitoring two or more gases simultaneously, and thus a single chemical sensor is not sufficient; for environment applications, it is advantageous to monitor several gases simultaneously, and thus a multi-sensor system that integrates multiple chemical sensors into a single instrument is desired. Multi-sensors are also advantageous for supplementing measurements, and it is advisable to integrate the necessary electronic devices and air (or fluid) path components.

An e-nose is a broadband sensor array sensitive to a wide range of VOCs and gases and is a software–hardware system that combines multiple, locally selective sensors and pattern recognition algorithms to selectively quantify or distinguish gases and odors [112]. The sensor array may be a mixture of electrochemical and resistive sensors, or all sensors may be of the same type. The sensors are placed in a sensing chamber into which ambient air is drawn by a pump or fan. Some systems provide a collection of sensors appropriately selected for a specific application, such as volcanic eruptions. In addition to air pollution diagnosis, e-nose applications include medical diagnosis, food quality control, odor classification, and industrial odor measurement [113–116].

Burgués et al. integrated a portable e-nose system into a drone using dynamic sensor signals under flight conditions to train a machine-learning model for real-time odor measurements in wastewater treatment plants [9,117]. The e-nose was equipped with 21 chemical sensors, a GPS receiver, and a wireless communication system for real-time data transmission [9]. The measurement signal is transmitted to the ground station in real-time, and the designed partial least squares (PLS) model analyzes the data in real-time. This approach provided higher accuracy than the conventional steady-state correction method.

The recent advances in deep learning have greatly improved the real-time capabilities of gas sensors, especially e-nose systems. Deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) allow for streaming data input and automatic feature extraction, enabling real-time processing and prediction. For example, although not using a drone, Kang et al. [118] achieved the real-time detection and analysis of six gases, with a minimum response time of 1 s and an accuracy of 98% for CO, and Lee et al. [119] used a CNN model to detect ethanol and NO₂ within 10 s, and acetone and methanol within 30 s. A multi-task synthetic neural network designed by Wang et al. [120] requires only a few seconds of response data to be fed into the model to distinguish between gas type, concentration, and state predictions, and the model is trained using data from over 10 million sensors [121]. With baselines automatically tracked,

the e-nose can predict 12 VOCs with up to 95% accuracy by inputting 4 s of data during the response period and output the results in real time.

The sensor chambers required to accommodate multiple sensors can increase the response time of the system and power consumption can also be an issue. There have been attempts to use portable e-noses with small detection chambers mounted on drones. In this application, it is important to design customized, miniature chambers that enable rapid measurements [1,122].

The advantage of mounting the e-nose or a single sensor on a drone is that long-time drift has less impact on the performance of the chemical detection; when using a drone, the change in output, such as resistance or intensity, appears quickly over time as it passes through an area where the concentration of the molecule increases, and thus it is relatively less affected by long-term drift, which is a big advantage of drone applications.

5. Effects of Temperature, Humidity, and Airflow on Chemical Sensors

Temperature is a very important environmental factor for most chemical sensors. In many cases, the sensor's own resistance, fluorescence intensity, electrochemical impedance, light collection efficiency, and noise level may be temperature-dependent; the sensor temperature fluctuation associated with external temperature fluctuations may cause an unexpected signal [21,123]. For this reason, most resistance-type sensors operate at fixed temperatures and some IR absorption apparatuses also have a temperature control function. In the concentration analysis, one should consider the rate of molecular outflow rate (if target molecules flow from the source) and the equilibrium vapor pressure depending on the external temperature.

Humidity is also a very important environmental factor, and the resistance and sensitivity of MOS sensors can be affected by the adsorption of water molecules onto MOS, or the deterioration of the sensing materials can be accelerated. In the case of electrochemical sensors, the concentration of the electrolyte can change, or the electrochemical reaction can change as water molecules penetrate into the electrolyte. In the case of optical sensors such as NDIR, if a wavelength of low absorption by water vapors is selected, it may theoretically be hardly affected by humidity, but the output and spectrum of the IR light source, the sensitivity of the detector, etc., may be affected by temperature. In addition, if the humidity is excessively high, water condensation on optical components may disturb signals [21,124].

One way to reduce environmental impact is to install a system that can always keep factors such as temperature and humidity of the sensor constant [125,126]. It is relatively easy to control the sensor temperature using a heater or a thermoelectric device. In particular, MEMS sensors using MOS are generally equipped with heaters to maintain high operating temperatures. The most common method is to use Joule heating to the side or base layer of the sensing material, but there are also cases where a self-heated structure is adopted to improve energy efficiency [127,128].

If external air is introduced into a sample chamber for measurements, a heating and dehumidification system may be required for temperature and humidity control. In addition, care must be taken because molecules may adsorb on the walls of the chamber, or a hose, which may affect the measurement. In the case of humidity, it seems difficult to completely control the humidity of the air sampled from the outside.

Although the humidity can be controlled by mixing with dry air to adjust the desired humidity, or by using a desiccant (silica gel, etc.) filter, a moisture-permeable filter, or other air conditioning systems, the measurement may be adversely affected if the concentration decreases or the composition changes due to the dilution process or adsorption of the analyte [129]. In addition, the volume, weight, and power consumption of the measurement

system may increase, and molecules may be adsorbed on the walls of the chamber or hose, affecting the measurement.

Figure 13 demonstrates how sensor signals change due to environmental factors. Figure 13a shows the change in fluorescence intensity over time and the quenching response to repeated DNT vapor outflow, which was controlled by the shutter in the fluorescent quenching method. The temperature was constantly changing via a heater operating in the room, and the temperature was recorded by a temperature sensor mounted inside the equipment; it was confirmed that the fluorescence intensity decreased as the temperature increased [21].

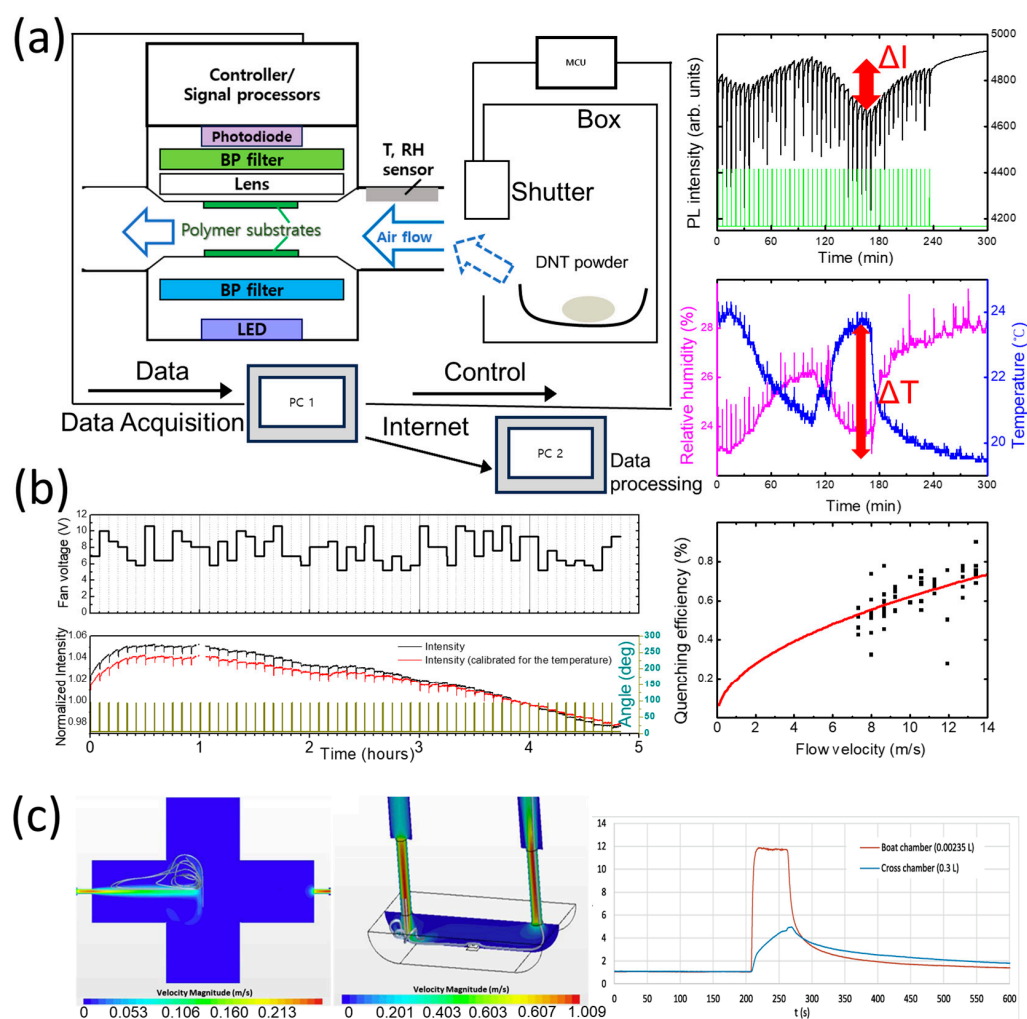


Figure 13. (a) Explosive detection by fluorescence quenching method using shutter control and the impact of temperature variation on intensity. (b) Fan voltage and fluorescence intensity as a function of time (left) and fluorescence quenching efficiency with respect to airflow (right) (c) Effect of chamber structure on MOS sensor response. Computational fluid dynamics simulation results (left) and sensor response (SnO₂ sensor exposed to 50 ppm of ethanol) depending upon the chamber structures [130]. Copyright 2019 by Elsevier. Reprinted with permission.

Flow rate is also an important factor that can influence the measurement both in the vapor and in the liquid phases. In our previous study, the effect of airflow on fluorescent quenching in a conjugated polymer explosive vapor sensor was studied. Figure 13c shows the effect of flow velocity on fluorescence quenching. The sensor operated at room temperature in a near-open environment. The increase in the quenching degree with the increasing airflow was attributed to the increase in the molecular diffusion rate from the air to the polymer film [20]. The effects of flow rate and molecular diffusion are expected to be

observed not only in polymer sensors but also in other sensors where molecular adsorption and desorption processes are important.

In our previous study, the flow distribution was considered a laminar-like flow between two plane sensor substrates. However, in general, the chamber structure and the flow velocity profile affect the sensor response. Figure 13c shows a comparison of the flow distribution and SnO₂ gas sensor response under exposure to ethanol [130]. The results of the research by Annanouch et al. in Figure 13c show that it is necessary to optimize the chamber structure to ensure proper sensing performance, including sensitivity, response time, and detection limit. Mahdavi et al. numerically analyzed how internal flow is affected by the chamber geometry and sensor location, and investigated the surface temperature, response speed, extent of sensor response, and optimum working temperature based on the flow rate [131].

Robbiani et al. reviewed in detail various physical factors that can affect the e-nose signals, such as temperature, humidity, flow rate, chamber design, and sampling method, and emphasized the importance of the optimal design of customized hardware systems [132].

Improving the measurement system in terms of hardware, such as a direct control system of temperature, humidity, and chamber design, is expected to help obtain high-quality sensor data with less interference from environmental factors. However, such hardware design may have limitations in terms of volume, weight, power consumption, and cost. In particular, weight and power consumption are important considerations for a drone, or for a portable system. In such cases, it may be preferable to compensate for the influence of the external environment through software.

For the short-term correction of temperature and humidity variations, the sensor can be calibrated using previously measured data, or the signal can be corrected using machine learning techniques based on the measured data. Liu et al. were able to compensate their sensor data using local Gaussian process regression for a polyaniline-cerium dioxide (PANI-CeO₂)-based NH₃ sensor [133]. Figure 14a shows the schematic structure of the model.

According to the authors' measurement results, when the PANI-CeO₂ NH₃ sensor used in the experiment is used to compensate for the temperature and humidity using linear regression, a large error of about 17.33 ppm occurs, but the response value residuals show an approximately normal distribution. In this case, the Gaussian process regression (GPR) algorithm can be used to compensate for temperature and humidity. GPR is a technique that simultaneously models the distribution of a function and the prediction uncertainty based on given data, assuming that the data are sampled from a Gaussian process. By repeatedly updating the posterior distribution according to new data through the Bayesian theorem, the function explaining the data and the deviation can be derived.

In this study, the authors increased the data density using interpolation and reduced the computational complexity of GPR using the K-nearest neighbors (KNN) technique. KNN is a machine learning technique that predicts the properties of the data from existing data by selecting the data point with the smallest Euclidean distance to a specific data point, that is, the closest data point. The flowchart shown in the middle of Figure 14a shows a series of processes for correcting signals using a local GPR model. Data including temperature, humidity, and sensor signals are processed through KNN and GPR after going through the interpolation process. Here, the number of neighboring points used in KNN was adjusted from 45 to 5, and the reliability was the highest when K = 15. A detailed explanation of KNN is covered in the next section.

For long-term signal drift, more efforts are required for data acquisition and sensor signal correction. In particular, irreversible changes in the sensor due to factors such as excessive exposure to analytes, or excessively high/low temperature and humidity conditions, may complicate both signal processing and sensor maintenance. Additionally,

even in non-extreme environments, the rate of sensor degradation can be affected by temperature; Papaconstantinou et al. observed that performance degradation in commercial electrochemical sensors was relatively faster in summer when temperatures were high [134]. Figure 14c indicates the correlation between the low-cost sensor signals and the high-accuracy reference instrument signals for CO sensors. The figures showing signal drift over the course of a year are presented at the bottom [134].

The cause of the signal drift is known to be a complex interaction of physical and chemical factors depending on the sensor structure and materials. In the case of MOS sensors, it is known that chemical factors such as diffusion of oxygen and oxygen vacancy and cracks occurring in particle grains are involved [135].

The time-dependent aging phenomenon can be improved by replacing the sensor material. Figure 14b shows the time-dependent aging effect of SnO₂ performed by Nelli et al. The top and bottom graphs correspond to without and with gold doping, respectively, and the aging effect in air seems to be less in the case of no doping, but the aging effect under CH₄ gas exposure conditions is confirmed to be relatively improved in the case of doped SnO₂ [136].

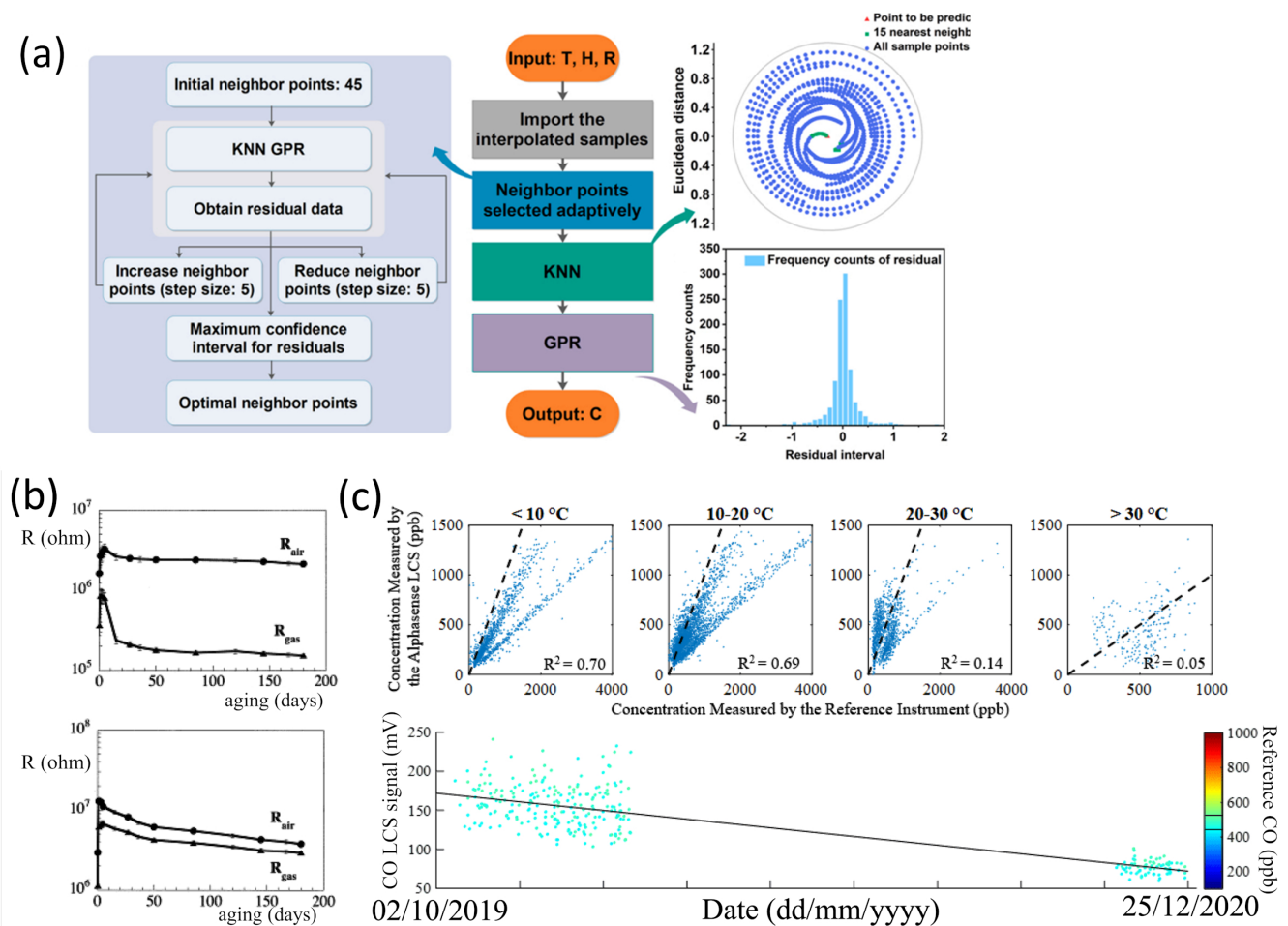


Figure 14. (a) Temperature and humidity effects correction using Gaussian process regression (GPR) [133]. Copyright 2022 by Elsevier. Reprinted with permission. (b) Time-dependent drift and response degradation of SnO₂- and Au-doped sensors. Degradation can be controlled by doping [136]. Copyright 2000 by Elsevier. Reprinted with permission. (c) Correlation between CO measurements recorded by a commercial electrochemical sensor and by a reference sensor. The drift of signals for CO and NO₂ over a period of a year [134]. Copyright 2023 by Papaconstantinou et al.

Regarding the hardware aspect, efforts to improve sensor materials can reduce the drift, but it is difficult to completely prevent the drift. Therefore, software compensation for sensor drift may be necessary.

Koziel et al. studied the drift of NO₂ electrochemical sensors after long-term use and its compensation using machine learning. They aimed to calibrate the data of low-cost electrochemical sensors close to the reference data [137]. The electrochemical sensors were installed at the same location as the reference and were calibrated with the reference data obtained from precise monitoring stations. The low-cost platform included electrochemical sensors (one primary sensor and two auxiliary sensors) and environment sensors (temperature sensors for inside and outside of the platform and atmospheric pressure sensors). Figure 15 shows the artificial neural network (ANN)-based structure of the correction model and the correction results that they observed. To reduce the statistical differences between the low-cost electrochemical sensor data and the reference data, statistical pre-processing was performed using nonlinear transformation. The pre-processed electrochemical sensor data and environmental sensor data were processed through an ANN model with three fully connected hidden layers (expressed as calibration surrogates) and Kriging interpolation, and the outputs of each were linearly mixed to obtain the final result as an output. They evaluated model performance for various hyperparameters and found that the advanced model showed excellent performance, with a high correlation coefficient of 0.95 and a low RMSD of 2.4 µg/m³ compared to the reference data.

Another method for drift correction is adaptive drift correction, which continuously updates the sensor compensation model using new measurement data. Kwon et al. conducted a study on the compensation of the e-nose composed of a MOS sensor using the adaptive drift correction strategy [138]. For the e-nose sensor data, they used a publicly available dataset collected in the study of Vergara et al. [139], which included a 128-dimensional feature vector obtained through feature extraction using the exponential moving average method. Figure 16a shows the concept and correction results of the drift correction strategy used by Kwon et al., and Figure 16b represents the process of feature extraction. Here, the encoder part of the masked-autoencoder, whose input and output are 129-dimensional data of a 128-dimensional feature vector and a concentration value, was used as the calibration feature encoder (CFE). The CFE output, which is the latent vector of the masked autoencoder, was used together with the sensor signal as input to the multi-layer perception for concentration estimation. The study was conducted by dividing the dataset into three.

Dataset-A contains data from 1 to 20 months, while dataset-B and dataset-C contain data from 21 to 23 and 24 to 36 months, respectively. Dataset-A was used for learning, and dataset-B and dataset-C were used to evaluate the drift correction capability. CFE was trained first, and then multilayer perceptron (MLP) was trained using the drift feature generated using CFE.

In the evaluation of six types of analytes (ethanol, ethylene, ammonia, acetaldehyde, acetone, and toluene) as learning results, they confirmed that on average, the root mean square error (RMSE) of the model using the masked-autoencoder showed a smaller error than that of the general autoencoder, MLP or PLS alone, or MLP plus PLS similar to MLP-CFE. Compared to the case of using an autoencoder without a mask, in dataset-B, the case without a mask showed a lower RMSE on average, but in dataset-C, the case with a mask showed better results.

There were other studies to minimize the environmental effects of chemical sensors. For example, in the case of MOS sensors, temperature modulation and UV-LED excitation modulation methods are known to be effective in improving selectivity, cross-sensitivity, and noise and drift stability [140–142]. Other techniques, such as impedance measurement, can also enhance the environmental stability of MOS gas sensors. Potyrailo et al. utilized

the impedance measurement technique to improve the sensors' dynamic range and stability [143]. They used various SnO_2 sensors and tested them under numerous gaseous species (including ethanol and methane), humidity levels, and temperature conditions. The experimental results of Potyrai et al. showed improved stability under varying humidity and ambient temperature conditions using the impedance measurement technique compared to static measurement. One of the interesting findings from Potyrai et al.'s research is the self-compensation effect observed in the rear part of the impedance response at a specific operating frequency (2.7 MHz). This self-compensation effect demonstrated strong compensatory ability and did not require additional hardware, such as heaters or LEDs.

In addition to the results described above, there are various techniques for the drift correction of chemical sensors or e-nose, and Rudnitskaya classified and reviewed the techniques used in various studies in detail [144].

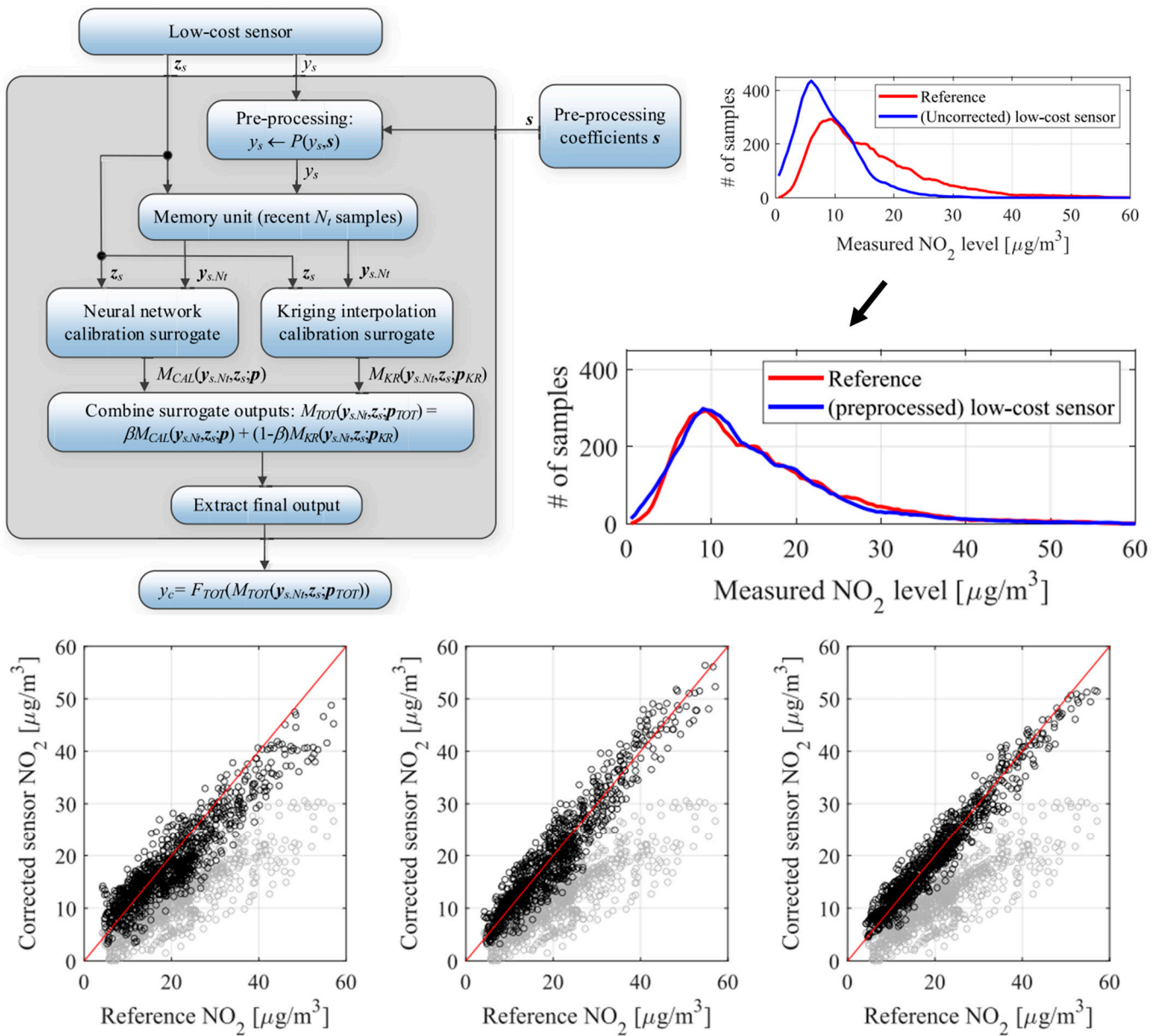


Figure 15. ANN-based drift correction model and correction results [137]. In the scatter plots at the bottom, the gray (black) colors indicate uncorrected (corrected) data. Copyright 2024 by Koziel et al.

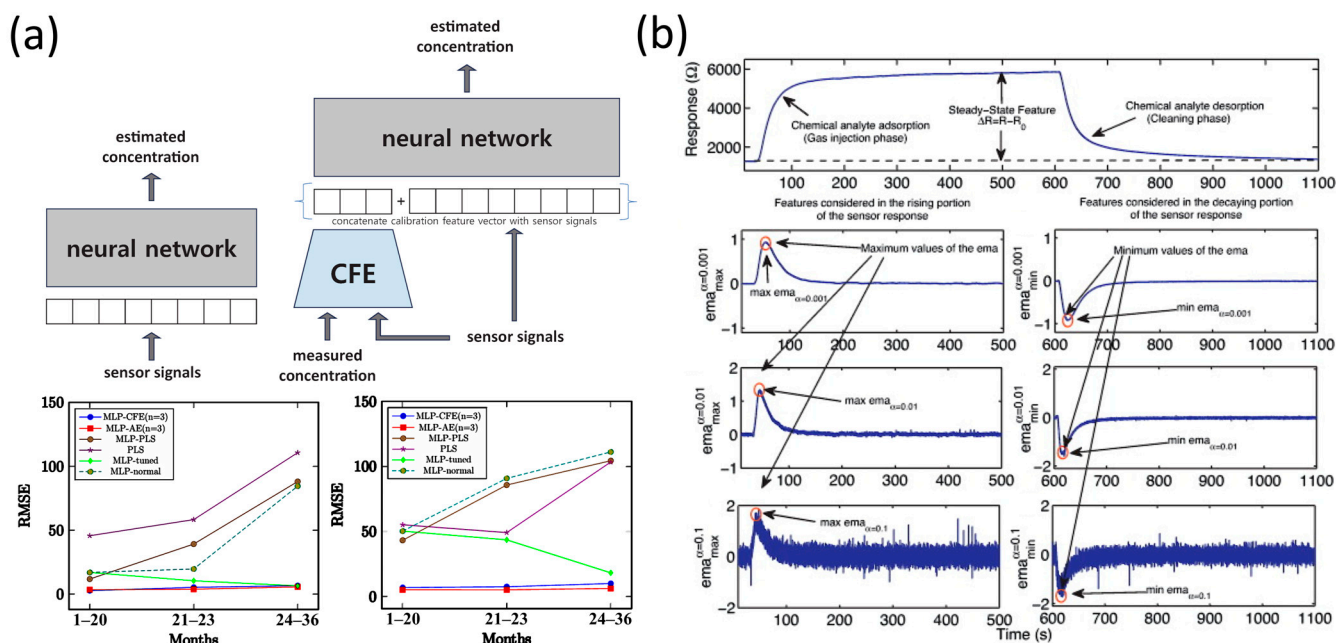


Figure 16. (a) Drift compensation model using ANN, calibration feature encoder (CFE) that extracts drift characteristics, and RMSE of compensation results [138]. Copyright 2024 by Kwon et al. (b) Exponential moving average feature extraction from long-term period data measured from a MOS sensor array [139]. Copyright 2012 by Elsevier. Reprinted with permission.

While we have discussed the effects of temperature, humidity, and airflow on sensors, there are also challenges that arise when mounting sensors on drones. As we discussed in the previous section, most air-borne gas sensing may be influenced by airflow and air-mixing associated with the drone's speed and types. For most fluorescence and NDIR methods, air is drawn into a chamber through an air intake either built-in on the drone or a pylon mounted on the base of a drone. In the case of a multicopter drone, strong turbulence is formed under the drone, actively mixing the air underneath the drone. In this aspect, fixed-wing drones may be preferred, but may be limited in their ability to hover and fly in the required area.

6. Machine Learning Techniques for Sensor Data Processing

In Section 6.1, we illustrate why data processing is necessary for sensors mounted on mobile platforms, and in Section 6.2, we introduce gas boundary tracking using wireless sensor networks (WSNs). In Section 6.3, we briefly describe some techniques in machine learning. Section 6.4 (resistive and electrochemical sensors) and Section 6.5 (optical and image sensors) examine cases where machine learning has been used to improve the selectivity of various types of sensors, although they are not directly applied to drones.

6.1. Is Data Processing Necessary for Mobile Platform Applications?

The main purpose of installing chemical sensor units on UAVs, or on robots, is to map the spatial distribution of target molecules (pollutants, hazardous gases, natural gas, biogenic substances (CO₂, methane), etc.) or to trace the source of leakage. For spatial mapping or chemical source localization, various algorithms and strategies for data processing and drone movement are utilized. The movement algorithm of the drone called taxis is a term meaning the movement of a living organism due to a stimulus, and can be categorized into phototaxis, thermotaxis, and gravitaxis (light, heat, and gravity, respectively) depending on the type of stimulus. Examples of applications to drones include a method for determining the direction of movement based on the concentration and rate

of change of chemicals (chemotaxis), a method for determining the path of movement by additionally considering the direction of the wind (anemotaxis), and a method for determining the path of movement in a direction that reduces uncertainty by calculating the entropy of the measured chemical signal (infotaxis) [1,2,145,146].

Park et al. improved the algorithm by prioritizing exploitation behavior to obtain higher concentration values at the expected source location instead of the traditional infotaxis approach using Gaussian mixture model (GMM) [147]. They estimated the source term using the particle filter technique based on Bayesian inference and evaluated the amount of information that the sensor can obtain at the location using the information-theoretic utility function. In a typical infotaxis process, the direction is set to maximize the information gain or the entropy reduction. In this process, infotaxis is often designed based on a discrete domain, so it determines the next action within a relatively limited set of actions (e.g., up, down, left, and right).

In the GMM-infotaxis process, the particles generated from the particle filter are clustered through GMM, and the source location is estimated using the average of each cluster. Using the source location estimated by GMM, an action set containing candidates for the next movement direction in the continuous domain is constructed, and among these, the action that maximizes the reduction in the entropy is selected. The authors conducted Monte Carlo simulations and outdoor flight experiments on infotaxis and GMM-infotaxis. In the outdoor experiments, a quadrotor UAV and multiple gas sensors (GSAS61-P110) Ogam Technology, Jinwon-myeon, Republic of Korea) were used, and acetone vapor was used as a detection target. The RMSE of the location as a result of 10 repeated measurements was 4.24 m and 1.10 m for each method, and the RMSE for release rate was also 1824 mg/s and 486 mg/s for each method.

Ma et al. compared the zigzag algorithm and the silkworm algorithm, which are types of anemotaxis algorithms, and showed that combining the two could achieve better source tracking performance [148]. According to the authors' analysis, the zigzag algorithm and the silkworm algorithm have limitations such as not being able to find the plume boundary due to the continuous change in the atmospheric environment or moving in the crosswind direction and stopping when the movement area is narrow, and detection fails during the search process. The zigzag-silkworm algorithm improved by the authors is similar to the silkworm algorithm, but the vertical sway is 30° to 60° , unlike the silkworm algorithm, which has a 90° angle to the windward direction. Therefore, it moves in a zigzag pattern when the gas concentration is not detected. As a result of comparing each algorithm, the results of 20 repetitions of the simulation showed that the zigzag-silkworm algorithm showed a smaller position error of 5.71 and 5.96 compared to the other two algorithms (8.16 and 8.15 for silkworm and 15.40 and 13.52 for zigzag).

For actual measurements, the position error of the zigzag-silkworm algorithm was 44 cm, which was not a significant improvement over the other two algorithms (27 cm for silkworm and 51 cm for zigzag), as measured 10 times on a ground-based mobile robot equipped with two MQ-3 (Risym) gas sensors (SnO_2 -based sensors). However, the detection success rate was 80%, which was a significant improvement over the other two algorithms (60% for silkworm and 50% for zigzag).

As in the two studies introduced above, when attempting to obtain the concentrations in real-time according to location using a mobile platform, the sensor response time and data acquisition time at each point can be important factors. The response time and recovery time of the sensor used in the study by Ma et al. were less than 5 s and 10 s, respectively, and the time to measure the concentration and complete the next rotation was about 8 s for the robot platform they used, so the response time of the sensor was not an issue in this case.

However, the response time of the sensor used in the study by Park et al. was 10 s, and data were collected for 3 s at each sampling position. Although the data acquisition time was shorter than the response time of the sensor, Park et al. claimed that the acquisition time of 3 s is sufficient time to obtain meaningful concentration values, averaged from five sensors on the drone, based on their measurement results, and that the limitations due to the slow response of the sensor can be partially overcome depending on the software technique used, such as “The use of the particle filter helps to compensate for the limitation of the slow gas sensor for source term estimation”. Chemical source localization and mapping have been reviewed in detail by Burgues et al. [1,149] and Adam Francis et al. [2].

The movement strategies of drones are very important in real-world measurements, but for the movement strategies to work effectively, it is necessary to obtain a sufficient amount of information quickly and accurately using sensors. Especially for measurements in an outdoor environment, the wind speed, chemical distribution, and the drone’s position all change over time, and thus, the sensor response must be fast enough to reflect these changes, and for gas measurements, a high sensitivity is required to detect target gases diluted in the air.

In addition, for accurate measurement, one may need to minimize problems such as the sensor’s cross-sensitivity, or matrix effect, and also have to appropriately compensate the sensor signal to take care of the environmental impacts described in the previous section.

6.2. Wireless Sensor Networks and Gas Boundary Tracking

In the case of source localization using a single UAV or a single robot, as described above, the source can be tracked using a localization algorithm. For other applications (such as gas boundary tracking) which require more information, a wireless sensor network (WSN) composed of a number of sensors and mobile devices can be utilized.

In a WSN, a device equipped with a sensor acts as a basic unit of the network called a node. Since the detection efficiency can vary depending on the distance between each node, spatial distribution, and movement strategy, it is important to optimize the algorithms for the wireless communication and positioning.

When analyzing the diffusion of gaseous substances using a WSN, it can be helpful to utilize a gas distribution model. Gas distributions are frequently assumed to be continuous objects, and various models (Gaussian model, puff model, 3D-finite element model, Sutton model, gas turbulent diffusion model, etc.) can be used depending on static and dynamic environments, and heavy and light gas clouds [150].

Shu et al. reviewed source localization and boundary tracking using WSNs in gas leakage situations [150]. The review specifically discussed the advantages and limitations of each algorithm, including the gas distribution model, and presented challenges to be solved in source localization using WSNs (including the effects due to turbulence and obstacles and the need for further research on continuous object detection in 3-D space). In addition, there were other studies which proposed a method to determine the boundary area using planarization algorithms such as relative neighborhood graph (RNG) and Gabriel graph (GG) [151], and compared the dangerous area estimated by planarization algorithms (RNG, GG, Delaunay graph, localized Delaunay graph, and Yao graph) according to the number of nodes, gas diffusion radius, and failure ratio of detection through simulation [152].

Liu et al. conducted a study on boundary tracking using machine learning techniques, binary tree (BT) and SVM [153]. They explained network partitioning using a full BT structure. In this approach, the sensor adaptively adjusts the size of the partitioned cell according to the size of the area where the signal changes (event area) by detecting leaked gas, etc. Subsequently, the boundary tracking problem is transformed into a binary classification problem in a two-dimensional Euclidean plane, and a hierarchical soft-margin SVM

is introduced to estimate a specific boundary shape. They evaluated their algorithm using simulation and found the results showed that the binary tree structure-based continuous object boundary tracking algorithm (BTS-COT) can reduce the number of nodes required for boundary tracking by about 50% compared to other methods (TGM-COT [154], VF-POD [155], and BRTCO [156]), and it is inherently robust to false sensor readings even for high ratios of faulty nodes (~9%) [153].

Most research on gas boundary tracking using WSNs has been conducted through simulations. Unfortunately, the construction of WSNs using UAVs still seems to be a challenging task. As Shu et al. pointed out, the lack of research on 3D WSN control and data processing algorithms applicable to UAV networks, along with the need for a reliable UAV automatic control system to prevent collisions or damage and ensure long-term operation, contributes to this difficulty. In addition, the high initial cost of UAV networks compared to the stationary sensor platforms and the significant legal restrictions on UAVs (such as UAV weight and flight altitude) are also the limitations. As mentioned in the previous section, Park et al. conducted their study under the condition that “The UAV moves in a 2-D horizontal plane and the movement step size is 3 m at a fixed altitude of 2.0 m” [147]. However, such low flight altitudes may not be permissible in urban areas or regions with strict legal regulations.

6.3. Brief Introduction to Machine Learning Technologies

In order to improve sensor performance, in addition to improving sensor hardware, signal processing techniques using machine learning are being studied. Figure 17 shows a conceptual drawing of some machine-learning techniques, and Table 1 shows the corresponding explanations. In this section, we briefly summarize the main techniques in machine learning, and in the next section, we review specific cases regarding sensing technology, where the selectivity of various types of sensors has been improved through machine learning.

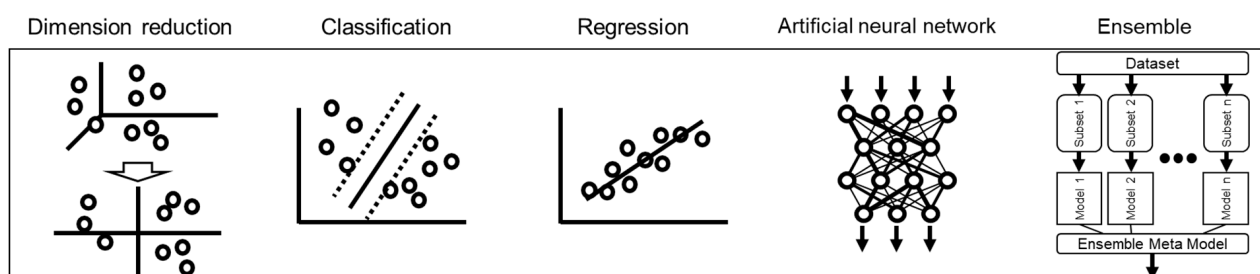


Figure 17. Conceptual drawing of machine learning techniques. From left to right, dimension reduction (e.g., principal component analysis), data classification (e.g., SVM), regression (e.g., linear regression), artificial neural network (e.g., deep neural network (DNN)), and ensemble learning techniques (e.g., bootstrap aggregation).

We would like to briefly explain dimension reduction, classification, and regression algorithms for data processing (Figure 17). Dimension reduction aims to preserve the information or characteristics of high-dimensional data and map it to a low-dimensional space. Principal component analysis (PCA) is a technique that preserves the variance in high-dimensional data as much as possible and projects it into a low-dimensional space. It is classified as unsupervised learning because it does not require predefined classifications or labels.

Table 1. Types of machine learning techniques and explanations.

Technique	Dimension Reduction	Classification and Regression		Neural Network	Ensemble
		Classification	Regression		
Output type	Data in a lower dimension	Classified label	Prediction value	Classified label, Prediction value, Extracted feature, Denoised data, etc.	Classified label, Prediction value, etc.
Dominant training types	Supervised learning, Unsupervised learning	Supervised learning	Supervised learning	Supervised learning, Unsupervised learning, Reinforcement learning	Supervised learning
Training variables and objects	Maximizing data covariance, maximizing between-class covariance and minimizing within-class covariance, Minimizing Kullback–Leibler divergence, etc.	Minimizing classification errors or Maximizing classification reliability	Minimizing errors between prediction and training data	Adjusting weights and biases to minimize a predefined loss function	Optimizing individual models within the ensemble
Algorithms	Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), t-distributed Stochastic neighbor embedding (t-SNE)	Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic regression, Naive Bayes, Decision tree	(linear, polynomial, exponential, and other) regression, functional regression, Support Vector Regression (SVR), Regression tree	Multilayer perceptron and Deep Neural Network (DNN), Convolution Neural Network (CNN), RNN (Recurrent Neural Network), Autoencoder, Transformer	Bagging (Bootstrap Aggregation), Boosting, Stacking
Nonlinear data processing	Using ‘Kernel trick’, Quadratic Discriminant Analysis (QDA), t-SNE	Using ‘Kernel trick’, KNN, Decision tree	Using ‘Kernel trick’, Nonlinear (polynomial, exponential, logarithmic, etc.) regression	Suitable for nonlinear data processing	Suitable for nonlinear data processing
Purpose of use	Data compression, Feature extraction, Data visualization (2~3 dimensional output)	Classification of data into pre-determined classes	Prediction of values not measured, theoretical analysis, and understanding of relationships between variables	Various models can be utilized depending on the purpose, including prediction (class labels, numerical values, future trends), feature extraction, and denoising	Improved model performance, robustness, and stability.

PCA aims to find a direction that maximizes the variance in the data, and the variance for a specific axis can be expressed through the covariance matrix, as follows:

$$X = \{x_1, x_2, \dots, x_n\}$$

$$\mu = \frac{1}{n} \sum_{i=1}^n x_i, \quad C = \frac{1}{n-1} \sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T$$

$$\begin{aligned} \text{Variance of the projected data} &= \frac{1}{n-1} \sum_{i=1}^n (v^T(x_i - \mu))(v^T(x_i - \mu))^T \\ &= \frac{1}{n-1} v^T C v \end{aligned}$$

x_i : the i th data in the dataset;

n : number of data in the dataset;

C : the sample covariance matrix;

v : a unit vector directing the projection axis.

Therefore, the variance in the projected data is equal to the Rayleigh quotient when $\|v\| = 1$ divided by $n - 1$.

$$R(v) = \frac{v^T C v}{v^T v}$$

The problem of finding the principal vector that maximizes variance can be transformed into the problem of finding the eigenvalues of the covariance matrix using the Lagrange multiplier method.

$$v_{optimal} = \underset{v}{\operatorname{argmax}} (v^T C v)$$

$$Cv = \lambda v$$

In PCA, the first principal component axis is determined by finding the eigenvector corresponding to the largest eigenvalue among the eigenvectors of the covariance matrix. Then, the process of finding the second principal axis in the direction orthogonal to the first principal axis is repeated so that each principal component is orthogonal to each other. By selecting some of the axes determined in this way and projecting the data, the dimensionality of the data is reduced while maintaining the distribution characteristics of the data.

Linear discriminant analysis (LDA) is a supervised learning algorithm that learns data with pre-labeled classes and then uses the result to perform dimensionality reduction or data classification. LDA aims to maximize the variance between classes and minimize the variance within classes.

Depending on the type of output you want to obtain by processing sensor data, you can use various machine-learning algorithms for purposes such as classification and regression. Classification is used to categorize data into predefined classes based on data characteristics, while regression is generally used for the purpose of predicting numerical values of data for a continuous domain. For classification, representative examples include support vector machine (SVM), KNN, and decision tree (DT).

SVM is a linear classification algorithm based on supervised learning that finds the most appropriate hyperplane to classify labeled data and classifies the new data based on it. SVM generally shows excellent performance, but problems may arise when the linear separation of data is difficult. In such cases, the issue can be addressed by using the kernel trick. Kernels expand the variable space to allow for nonlinear boundaries between classes. As the order of kernels increases, more diverse decision boundaries are created, such as polynomial kernels. The kernel trick is commonly used not only in SVM but also in other machine learning algorithms to handle nonlinear data.

KNN is a non-parametric supervised learning technique that selects a certain number (K) of data (nearest neighbors) with the closest distance between data points based on the assumption that new data points will have similar properties to existing data points with close distances and estimates the labels of new data, etc. Depending on the number of data K has selected, overfitting may occur (if K is too small) or generalization performance may decrease (if K is too large), so it is very important to select an appropriate K value. The distance between data is usually calculated using the Euclidean distance, but there are also cases where other types of distance metrics are used depending on the characteristics of the data, such as the Manhattan distance or a more generalized form of the Minkowski distance.

Artificial neural networks (ANNs) are AI models that mimic the structure of biological neurons. Typically, they consist of interconnected structures known as neurons, which receive multiple inputs and produce a single output. Depending on the intended

application, various model architectures can be designed by adjusting the connections between neurons and selecting activation functions. ANNs can accommodate a wide range of learning algorithms, including supervised learning, unsupervised learning, and reinforcement learning.

Furthermore, these models offer the advantage of being modifiable, allowing for the adaptation of existing models or the fine-tuning of pre-trained models. However, they are also susceptible to several issues, such as the black box problem, local minima problem, and overfitting problem. Prominent models include DNN, which enhances processing performance by stacking multiple neuron layers; CNN, which is frequently employed in image processing; and RNN, which is extensively used for sequential data processing.

6.4. Machine Learning Technologies for Resistive and Electrochemical Sensor Data Processing

Resistive sensors, especially MOS gas sensors, are one of the most widely commercialized sensors and have the advantages of small size, thermal and chemical stability in the air, and high sensitivity. However, much research is now being conducted to overcome high operating temperatures and the limitations of low selectivity. In particular, to address the problem of low selectivity, an approach that analyzes the data obtained from a multi-sensor array using machine learning to determine the concentrations and types of analytes is widely used.

In the case of Ma et al., a commercial e-nose system consisting of a total of 10 MOS sensors was used to sense and classify 10 types of VOC analytes (ethanol, methanol, isopropanol, N-pentane, N-hexane, furan, ethyl acetate, acetaldehyde, furan–ethanol mixture, furan–ethyl acetate mixture) [157]. The response to each analyte type and concentration of the e-nose system over time was processed in the form of an image, and classification was performed using a model that used error-correcting output codes (ECOC) and support vector machine (SVM) together, and a deep neural network (DNN, or deep learning model; DLM). When classifying analytes using a single sensor using ECOC and SVM, the accuracy was 29% when using a single data point, and 42% when using data measured by a single sensor for 600 s.

While the classification accuracy was not high when processing a single sensor signal, when using a sensor array, the accuracy was 81% when using one response data point for each sensor, and 87% when using all response points for 600 s, showing improved classification accuracy. When compared to other machine learning techniques, the classification accuracy of the convolutional neural network (CNN)-based DNN model was 92%, which was higher than when using ECOC and SVM together.

Viet et al. used a commercially available MOS sensor module and measured the sensor responses of eight gases (three high toxic gases, H_2S , SO_2 , and NO_2 , and five other gases, CO , H_2 , NH_3 , $\text{C}_2\text{H}_5\text{OH}$, and CH_3COCH_3) as a function of concentration. The sensor module consisted of a total of eight sensors, and the data obtained from them were used to evaluate the accuracy according to the classification algorithm using popular machine learning techniques (KNN, LSVM, KSVM, LDA, MLP, RF (random forest), DT, Gaussian naive Bayes (GNB), quadratic discriminant analysis (QDA), and gradient boosting (GB)) [158]. Comparisons were made depending on whether dimensionality reduction using PCA was introduced and the number of principal components (PCs) used after dimensionality reduction. Additionally, they evaluated the prediction accuracy of each algorithm according to the train/test split ratio.

As a result of comparing the algorithms, in the case of KNN ($k = 5$) and DT, the accuracy decreased when PCA was used, while LSVM, LDA, and QDA showed almost similar accuracy regardless of whether PCA was used. For the rest (KSVM, MLP, RF, GNB, and GB), higher accuracy was achieved when PCA was used, and in particular, GB showed

an excellent accuracy of 100% when three main PCs were used. KNN and LSVM were found to be less suitable for sensor data processing than other algorithms (accuracy of 0.62 and 0.59, respectively, without PCA processing), which is in contrast to other studies that reported excellent classification performance using SVM.

In the study by Khan et al., a Pt-, Cu-, and Ag-decorated TiO₂ and ZnO functionalized GaN nanowire-based sensor array was used to sense NO₂, ethanol, H₂, SO₂, H₂O, and O₂ gases, and instead of heating, a UV-LED was used [159]. They measured sensor responses according to gas inflow using an array equipped with eight types of sensors, and classified gas types from sensing data using DT, SVM (linear kernel), naive Bayes (kernel), and KNN (k = 1) classifiers. They evaluated the classification accuracy with a total of 50 pieces of measurement data and showed that SVM and NB accurately classified all measurement results.

However, it may be difficult to directly compare the two studies because the data preprocessing methods and hyperparameters used in the machine learning models may be different, and the classification results using machine learning may be significantly affected depending on the type of sensor, operation method, and sensing target material. Another point to consider is the dimensionality of the sensing data. The two studies introduced above used eight sensors to obtain the data, which represent relatively low-dimensional data compared to image sensors that have to process hundreds, thousands, or even tens of thousands of pieces of data. As the number of sensors increases and the dimensionality increases, data complexity, redundant information, noise generated from individual sensors, and the phenomenon of blurring the distinction between data due to distance, commonly called the curse of dimensionality, can occur, and thus these factors must be considered together when selecting a machine learning algorithm.

In addition to array-type sensors, there are also studies that analyzed the transient characteristics of sensors that actively control external conditions using machine learning to perform classification and concentration estimation [142,160]. Cho et al. fabricated a photoactivated gas sensor by depositing nano-porous In₂O₃ on a micro-LED (~395 nm) using a glancing angle deposition technique and then coating it with gold nanoparticles [142]. The authors performed measurements on the following five gases: air, methanol, ethanol, acetone, and NO₂. They controlled the micro-LED with five levels of pseudorandom operation to measure the transient response of the sensor. After the Fourier transformation of the response data, the data were used to train a deep convolutional neural network (D-CNN) model. The data measured during a time window of 60 s were preprocessed and input to the D-CNN model. In the D-CNN model, classification and regression were performed simultaneously to obtain the class and concentration of gas as output. A classification accuracy of more than 85% was obtained for each gas, and a regression coefficient of $R^2 = 0.888$ was obtained for all test gases.

Additionally, the authors conducted tests on mixed gases, with different ratios of ethanol and methanol mixed gases. The output of D-CNN was modified to display the normalized concentration of gas and its presence as a confidence score. As with the single gas test, the experiment was conducted using pseudorandom operation, and the accuracy of 97.63% and 98.68% for the presence or absence of gas was obtained for methanol and ethanol, respectively. For concentration, the mean absolute percentage error values were 36.8% and 32.3% in the unmixed pure gas state for methanol and ethanol, respectively.

Compared to resistive sensors, electrochemical sensors are known to have relatively high selectivity, but it is difficult to perfectly distinguish between types of substances, and they are not completely free from problems such as cross-sensitivity and matrix effects. Another limitation of electrochemical sensors is the potential for electrode contamination

over time. Machine learning may be one way to overcome the complexity of signal disturbance or compensation due to these factors [161,162].

Electrochemical sensors are mostly composed of three-electrode systems and monitor current as a function of applied voltage, and depending upon how the voltage is controlled, electrochemical measurement methods can be classified into CA, CV, DPV, and EIS.

Xu et al. fabricated an Au nanoparticle/poly (L-Arginine)/reduced graphene oxide/glassy carbon electrode for the purpose of detecting chloramphenicol (CAP), an antibiotic, and performed measurements [163]. The authors conducted a study to accurately measure the concentration of CAP, particularly in the presence of interference by metronidazole (MNZ), an antibiotic with a similar redox potential to CAP. They showed that measurement accuracy can be improved by processing CV, DPV, and CA measurement results using machine learning. From each measurement result, features such as reduction peak current, area enclosed, and reduction potential were obtained, and features with a high correlation with the concentration of CAP were selected and used as input for the ANN model.

According to the experimental results, when using only a single method, the R^2 between the calibration curve obtained by linear regression and the current value was 0.98, 0.98, and 0.97 for CV, DPV, and CA, respectively, in a situation where there was no interference by MNZ, indicating a relatively high sensing accuracy. However, in a situation where there was interference by MNZ, the R^2 was only 0.80, 0.69, and 0.36, indicating that the accuracy was noticeably reduced by the interference. On the other hand, the concentration calculated using ANN from the features of the three techniques showed a high correlation with the actual concentration ($R^2 = 0.99$ (MNZ = 0.5 mM)), and it was shown that concentration measurement was possible with a high accuracy of $R^2 = 0.95$ even in situations where the concentration of MNZ was diverse. Additionally, Xu et al. showed that when feature selection is performed based on Pearson correlation, the error is relatively small.

In addition to these studies, Kang et al. reviewed data processing of electrochemical sensors using machine learning in detail [164]. The authors provided specific examples of strategies to obtain more meaningful features (information-bearing features) and capture features with high correlation with desired information [163–167]. Additionally, they emphasized that the results of machine learning are highly dependent on the quality of the experimental data, and that machine learning can provide valuable output when there is at least a subtle correlation between the experimental data and the information sought, such as the identity and/or concentration of target species.

6.5. Machine Learning Technologies for Optical and Image Sensor Data Processing

As previously introduced in Section 3, optical sensing can include IR absorption, fluorescence, surface plasmon resonance, SERS, and image patterns, and the data output of optical sensors is in the form of intensity, frequency, spectrum, and image pattern. IR absorption technique has the advantages of being not much affected by temperature and humidity, having a fast response speed and high selectivity, and requiring no separate data processing after appropriate compensation. However, only certain types of chemicals can be measured, and the sensitivity is somewhat limited compared to other methods.

In the case of fluorescence or photoluminescence intensity measurement, there were cases where the concentration of the analyte was measured over time. On the other hand, for smartphone applications, most studies have been carried out in order to calibrate smartphone cameras by first measuring fluorescence intensity or spectral changes as a function of target concentration [168,169], and no additional data processing other than correction using regression, etc., may be necessary. However, in cases where surrounding

objects can affect the image (e.g., tubes or trays containing liquid, excitation light reflected from surfaces, etc.), unlike when using paper-based sensors or microfluidic systems, data processing using machine learning may be helpful.

Mousavizadegan et al. studied fluorometric sensing using BSA-protected Au/Ag bimetallic nanoclusters (BSA-BMNCs) for sensing tetracycline [170]. Novel metal nanoparticles with very small sizes are known to be capable of photoluminescence or fluorescence due to quantum confinement effects. Their results showed that upon the reaction of BSA-BMNCs with tetracycline, emission near 645 nm was quenched, while green emission at 520 nm was maintained, resulting in a change in fluorescence color from red to green. They used a smartphone camera to capture fluorescence color changes, processed the data, and evaluated the concentration prediction accuracy using a total of five machine learning models (SVM, ANN, RF, Bagging + ANN, Bagging + DT). The accuracy of each model was different for water and milk samples. For water samples, Bagging + ANN showed the best accuracy with $R^2 \sim 0.998$, and for milk samples, Bagging + DT model showed the best accuracy with $R^2 \sim 0.997$.

Similar to the fluorescence methods, the colorimetric methods also measure either spectra or apparent colors, using spectrometers or image sensors. In particular, array-type or strip-type test paper sensors that analyze various chemicals at once have been used in various health screening scenarios because they are easy and convenient to use. However, colorimetric sensors are also difficult to quantitatively analyze and require the hassle of comparing colors one by one with a comparison table. In particular, the influence of external lighting can be problematic in obtaining accurate sensor values, and using specially designed mounts to address this can hinder the ease of measurement. Therefore, there have been studies to overcome this problem using smartphone cameras and machine learning techniques.

Mutlu et al. addressed the problems associated with conventional image correction and proposed to use machine learning to solve the problem [171,172]. They purchased commercial pH strips and took pictures of test paper colors according to solutions prepared at specific pH levels with a smartphone camera and compared the discrimination accuracy with and without some attachments made with a 3D printer, depending on the type of machine learning model (SVM and least-squares SVM). For machine learning, they used a classifier model that classifies pH into integers between 0 and 14. While the area under the curve (AUC) of the receiver operating characteristic curve of SVM was up to 0.9729 (JPEG) depending on the type of image format, the classification accuracy using least-squares SVM was 100% ($AUC = 1$). The authors also conducted additional studies on the light source effect. The least-squares support vector machine (LS-SVM) model trained using a single light source (smartphone flash) was applied to classify images captured under a combination of two of three lighting conditions, namely, sunlight, fluorescent, and halogen in the pH range of 4 to 9. The accuracy was significantly reduced compared to the single light source condition, but the classification accuracy was over 80% under the fluorescent–sunlight condition.

Besides these results, Jiang et al. developed a dye-based odor sensor array that can estimate the freshness of shrimp and fish by detecting VOCs in a gaseous state rather than in solution [173]. The authors fabricated a colorimetric sensor array in the form of a 4×4 array by selecting 16 kinds of chemo-responsive commercially available dyes that change color due to biogenic amines (BAs), such as NH_3 , dimethylamine (DMA), trimethylamine (TMA), cadaverine (CAD), and putrescine (PUT), which can be generated during the spoilage of aquatic products (Figure 18). To ensure the binding between the dye and the cellulose membrane, the authors prepared ammonium-quaternized cellulose nano-fibers (C-CNFs) using 2,3-epoxypropyltrimethylammonium chloride and bound the

dye-immobilized C-CNFs to filter paper through filtration. The sensor response for each BA was investigated and the detection limits were found to be 2, 21, 3, 1, and 1 ppm, respectively. They used CNNs to process data from this sensor. They argued that CNNs perform better than techniques such as SVM in high-dimensional data [172,173]. In this study, they used a model modified to obtain the final output of four classes (fresh, less fresh, slightly spoilt, spoilt) based on the ResNet-18 model [174], and fine-tuned the pre-trained model using ImageNet based on total volatile basic nitrogen (TVB-N), measured using the semi-micro Kjeldahl method). They used 10,148 images of shrimp, 10,125 images of fish, and 20,273 images of mixed shrimp and fish, of which 80% were used for training. They evaluated the performance of the model using test images (1666 shrimp, 1669 fish, and 3335 shrimp–fish mixtures), and showed that the degree of spoilage of fish and shrimp could be classified with up to 99.25% accuracy depending on the training dataset.

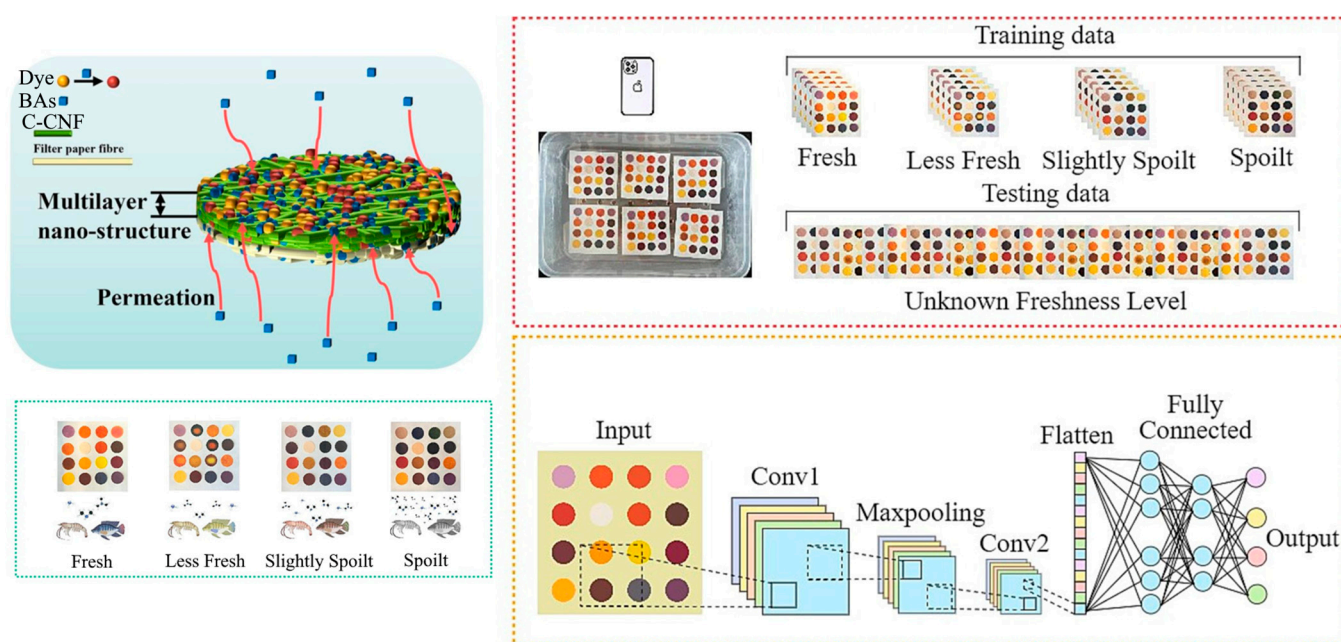


Figure 18. Conceptual illustration of dye-based colorimetric sensor arrays and neural network-based data processing technique [173]. The colorimetric sensor array (4×4 , total 16 different dyes) consists of dye-immobilized filter paper sensors, each with a diameter of 10 mm. Copyright 2024 by Elsevier. Reprinted and modified with permission.

7. Concluding Remarks

With the development of semiconductor and electric circuit technologies, sensors that measure physical elements such as image sensors and microphones have been widely installed in various platforms such as smartphones, automobiles, and drones, while the application of chemical sensors has been relatively limited. Nevertheless, chemical detection is a very important technology for public safety, medical, agricultural, and environmental monitoring, and efforts are being made to apply it to various platforms.

In this paper, the operating principles of resistive, electrochemical, IR absorption, and colorimetric chemical sensors, and their applications to drones and smartphones, are briefly discussed, and some specific research results are reviewed. Since the size of sensors that can be installed on mobile platforms is limited, accuracy, stability, limit of detection, specificity, and response time may be limited compared to expensive, large, heavy equipment, and we discussed the cases where machine learning was introduced to solve these problems.

In the case of smartphone applications, optical detection using smartphone cameras and electrochemical detection using external modules were often performed. Since smart-

phones equipped with high performance optical cameras are in common, they can be used for analyzing signals such as color changes in colorimetric sensors or fluorescence spectrum changes in fluorometry sensors. Some studies have demonstrated that more accurate chemical concentration measurements are possible by using external adapters to prevent signal interference or by using machine learning techniques to correct images.

Open path optical methods using lasers provide faster response speeds and are less affected by temperature and humidity than resistive or electrochemical methods, making them suitable for UAVs. In addition, since remote detection technologies such as back-scattered laser absorption spectroscopy can be used for long distance measurement, optical methods are often preferred for chemical detection applications using drones.

Drones, especially UAVs, have been utilized for chemical detections, but except for measurements in limited conditions such as inside greenhouses or buildings and gas leaks in pipelines, it still seems challenging to measure chemicals using resistive sensors or electrochemical sensors in a completely open environment. This is probably due to the stringent requirements such as the need for high sensitivity as gas is diluted in an open environment, the need to consider the downwash phenomenon caused by the drone's flight, whether the sensor response and signal recovery speed is sufficiently fast compared to the flight speed, and the need for a hardware/software system to respond to unpredictable changes in temperature and humidity in the open environment.

Another factor to consider in practical applications is that gas sensors may be affected by the mounting location and position in drone applications. For example, optical sensors can be greatly affected by vibrations that occur during the drone's flight and may need to be recalibrated whenever the optical system is misaligned. In addition, as explained above, the structure of the drone and the surrounding airflow must be considered when determining the mounting location of the sensor or chamber. In the case of UAVs, legal regulations on flights are non-technical issues, but they can be very important factors from a practical perspective. In many cases, aircraft including UAVs larger than a certain size are subject to regulations for safety and security reasons, and these legal factors may need to be considered in the overall design process of the sensing system, including drones, sensors, and flight algorithms.

In order to utilize UAVs for chemical detection in an open environment, the UAV and chamber structure must be considered so that measurements are not disturbed by airflow such as downwash. In particular, in terms of chamber design, the sensitivity and response speed of the sensor can be affected by the chamber volume and internal flow rate distribution, and thus the optimization of the chamber structure may be necessary.

In order to improve sensitivity and selectivity, various resistive sensor studies are also being conducted using nanomaterials such as graphene, TMDC, and nanoparticles, or using doping or hetero-semiconductor bonding. To overcome the limitations of a single sensor, many technologies have been developed to classify more accurate analytes from responses from multiple sensors using e-noses and to improve sensor accuracy. In particular, these e-nose systems are frequently used in drone or robot applications.

In many cases, data processing is performed through machine learning techniques, and ANN-based methods including CNN or DNN seem to show higher performance in classification accuracy than other techniques. As machine learning technology advances, many studies are being conducted on more accurate signal analysis and sensor compensation, and it is expected that the performance of e-noses and other sensors will be improved through data processing. In addition, continuous research on flight algorithms is necessary for practical applications such as source localization using UAVs. Finally, we would like to emphasize that when using drones, sensor outputs such as resistance or intensity can change rapidly over time as the drone passes over an area with an increasing concentration

of the chemicals, and thus reliability of chemical detection may be improved, which is an important advantage of using drones.

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References

- Burgués, J.; Marco, S. Environmental chemical sensing using small drones: A review. *Sci. Total Environ.* **2020**, *748*, 141172. [CrossRef] [PubMed]
- Francis, A.; Li, S.; Griffiths, C.; Sienz, J. Gas source localization and mapping with mobile robots: A review. *J. Field Robot.* **2022**, *39*, 1341–1373. [CrossRef]
- Hosseini Motlagh, N.; Kortoçi, P.; Su, X.; Lovén, L.; Hoel, H.K.; Bjerkestrand Haugsvær, S.; Srivastava, V.; Gulbrandsen, C.F.; Nurmi, P.; Tarkoma, S. Unmanned Aerial Vehicles for Air Pollution Monitoring: A Survey. *IEEE Internet Things J.* **2023**, *10*, 21687–21704. [CrossRef]
- Wasehun, E.T.; Hashemi Beni, L.; Di Vittorio, C.A. UAV and Satellite Remote Sensing for Inland Water Quality Assessments: A Literature Review. *Environ. Monit. Assess.* **2024**, *196*, 277. [CrossRef]
- Marin, D.B.; Becciolini, V.; Santana, L.S.; Rossi, G.; Barbari, M. State of the Art and Future Perspectives of Atmospheric Chemical Sensing Using Unmanned Aerial Vehicles: A Bibliometric Analysis. *Sensors* **2023**, *23*, 8384. [CrossRef]
- Debnath, D.; Vanegas, F.; Sandino, J.; Hawary, A.F.; Gonzalez, F. A Review of UAV Path-Planning Algorithms and Obstacle Avoidance Methods for Remote Sensing Applications. *Remote Sens.* **2024**, *16*, 4019. [CrossRef]
- Xue, J.; Mao, K.; Cao, H.; Feng, R.; Chen, Z.; Du, W.; Zhang, H. Portable Sensors Equipped with Smartphones for Organophosphorus Pesticides Detection. *Food Chem.* **2024**, *434*, 137456. [CrossRef]
- Ramírez-Coronel, A.A.; Alameri, A.A.; Altalbawy, F.; Sanaan Jabbar, H.; Lateef Al-Awsi, G.R.; Iswanto, A.H.; Altamimi, A.S.; Shareef Mohsen, K.; Almulla, A.F.; Mustafa, Y.F. Smartphone-Facilitated Mobile Colorimetric Probes for Rapid Monitoring of Chemical Contaminations in Food: Advances and Outlook. *Crit. Rev. Anal. Chem.* **2023**, *54*, 2290–2308. [CrossRef]
- Burgués, J.; Esclapez, M.; Doñate, S.; Marco, S. RHINOS: A lightweight portable electronic nose for real-time odor quantification in wastewater treatment plants. *iScience* **2021**, *24*, 103371. [CrossRef]
- Burgués, J.; Marco, S.; Doñate, S.; Esclapez, M.; Pastor, L. Drone-Based Environmental Odour Monitoring: SNIFFDRONE. Public Deliverable for the ATTRACT Final Conference 2020. Available online: <https://phase1.attract-eu.com/showroom/project/sniffdrone-drone-based-environmental-odor-monitoring> (accessed on 6 January 2025).
- Iwaszenko, S.; Kalisz, P.; Słota, M.; Rudzki, A. Detection of Natural Gas Leakages Using a Laser-Based Methane Sensor and UAV. *Remote Sens.* **2021**, *13*, 510. [CrossRef]
- Schuyler, T.; Bailey, S.; Guzman, M. Monitoring Tropospheric Gases with Small Unmanned Aerial Systems (sUAS) during the Second CLOUDMAP Flight Campaign. *Atmosphere* **2019**, *10*, 434. [CrossRef]
- Shah, V.; Bhaliya, J.; Patel, G.; Joshi, P. Room-Temperature Chemiresistive Gas Sensing of SnO₂ Nanowires: A Review. *J. Inorg. Organomet. Polym. Mater.* **2022**, *32*, 741–772. [CrossRef]
- Jaroń, A.; Borucka, A.; Deliś, P.; Sekrecka, A. An Assessment of the Possibility of Using Unmanned Aerial Vehicles to Identify and Map Air Pollution from Infrastructure Emissions. *Energies* **2024**, *17*, 577. [CrossRef]
- Rani Hemamalini, R.; Vinodhini, R.; Shanthini, B.; Partheeban, P.; Charumathy, M.; Cornelius, K. Air quality monitoring and forecasting using smart drones and recurrent neural network for sustainable development in Chennai city. *Sustain. Cities Soc.* **2022**, *85*, 104077. [CrossRef]
- Ramadan, M.; Basmaji, T.; Gad, A.; Hamdan, H.; Akgün, B.; Ali, M.; Alkhedher, M.; Ghazal, M. Towards early forest fire detection and prevention using AI-powered drones and the IoT. *Internet Things* **2024**, *27*, 101248. [CrossRef]
- Sheng, H.; Chen, G.; Xu, Q.; Li, X.; Men, J.; Zhou, L.; Zhao, J. An advanced gas leakage traceability & dispersion prediction methodology using unmanned aerial vehicle. *J. Loss Prev. Process Ind.* **2024**, *88*, 105276. [CrossRef]

18. McGonigle, A.; Aiuppa, A.; Giudice, G.; Tamburello, G.; Hodson, A.; Gurrieri, S. Unmanned aerial vehicle measurements of volcanic carbon dioxide fluxes. *Geophys. Res. Lett.* **2008**, *35*, L06303. [\[CrossRef\]](#)
19. Xi, X.; Johnson, M.; Jeong, S.; Fladeland, M.; Pieri, D.; Diaz, J.; Bland, G. Constraining the sulfur dioxide degassing flux from Turrialba volcano, Costa Rica using unmanned aerial system measurements. *J. Volcanol. Geotherm. Res.* **2016**, *325*, 110–118. [\[CrossRef\]](#)
20. Noh, D.; Ampadu, E.; Oh, E. Influence of Air Flow on Luminescence Quenching in Polymer Films towards Explosives Detection Using Drones. *Polymers* **2022**, *14*, 483. [\[CrossRef\]](#)
21. Noh, D.; Oh, E. Estimation of Environmental Effects and Response Time in Gas-Phase Explosives Detection Using Photoluminescence Quenching Method. *Polymers* **2024**, *16*, 908. [\[CrossRef\]](#)
22. Golston, L.; Tao, L.; Brosy, C.; Schäfer, K.; Wolf, B.; McSpirt, J.; Buchholz, B.; Caulton, D.; Pan, D.; Zondlo, M.; et al. Lightweight mid-infrared methane sensor for unmanned aerial systems. *Appl. Phys. B* **2017**, *123*, 170. [\[CrossRef\]](#)
23. Vivoli, E.; Bertini, M.; Capineri, L. Deep Learning-Based Real-Time Detection of Surface Landmines Using Optical Imaging. *Remote Sens.* **2024**, *16*, 677. [\[CrossRef\]](#)
24. Pryshchenko, O.; Plakhtii, V.; Dumin, O.; Pochanin, G.; Ruban, V.; Capineri, L.; Crawford, F. Implementation of an Artificial Intelligence Approach to GPR Systems for Landmine Detection. *Remote Sens.* **2022**, *14*, 4421. [\[CrossRef\]](#)
25. García-Fernández, M.; Álvarez-Narciandi, G.; Álvarez López, Y.; Las-Heras Andrés, F. Improvements in GPR-SAR imaging focusing and detection capabilities of UAV-mounted GPR systems. *ISPRS J. Photogramm. Remote Sens.* **2022**, *189*, 128–142. [\[CrossRef\]](#)
26. Sato, M.; Feng, X.; Fujiwara, J. Handheld GPR and MD sensor for landmine detection. In Proceedings of the IEEE Antennas and Propagation Society International Symposium, Washington, DC, USA, 3–8 July 2005; Volume 3B, pp. 104–107. [\[CrossRef\]](#)
27. Gonzalez de Santos, P.; Garcia, E.; Estremera, J.; Armada, M. DYLEMA: Using walking robots for landmine detection and location. *Int. J. Syst. Sci.* **2005**, *36*, 545–558. [\[CrossRef\]](#)
28. Ismail, A.; Elmogy, M.; ElBakry, H. Landmines Detection Using Autonomous Robots: A Survey. *Int. J. Emerging Trends Technol. Comput. Sci.* **2014**, *3*, 184–187.
29. Hugler, P.; Roos, F.; Schartel, M.; Geiger, M.; Waldschmidt, C. Radar Taking Off: New Capabilities for UAVs. *IEEE Microw. Mag.* **2018**, *19*, 43–53. [\[CrossRef\]](#)
30. García-Fernández, M.; López, Y.; Andrés, F. Airborne Multi-Channel Ground Penetrating Radar for Improvised Explosive Devices and Landmine Detection. *IEEE Access* **2020**, *8*, 165927–165943. [\[CrossRef\]](#)
31. Vikas Singh, P.; Moujan, I.; Kazi, A.; Kale, P.; Rode, S.; Pandey, A.; Mogal, S. A Review on Design and Characteristics of Landmine Detection Robot. *Evergreen* **2024**, *11*, 900–912. [\[CrossRef\]](#)
32. Boonkaew, S.; Szot-Karpińska, K.; Niedziółka-Jönsson, J.; de Marco, A.; Jönsson-Niedziółka, M. NFC Smartphone-Based Electrochemical Microfluidic Device Integrated with Nanobody Recognition for C-Reactive Protein. *ACS Sens.* **2024**, *9*, 3066–3074. [\[CrossRef\]](#)
33. Kalambate, P.; Larpant, N.; Kalambate, R.; Niamsi, W.; Primpray, V.; Karuwan, C.; Laiwattanapaisai, W. A portable smartphone-compatible ratiometric electrochemical sensor with ultrahigh sensitivity for anticancer drug mitoxantrone sensing. *Sens. Actuators B* **2023**, *378*, 133103. [\[CrossRef\]](#)
34. Monisha; Shrivasa, K.; Kant, T.; Patel, S.; Devi, R.; Dahariya, N.; Pervez, S.; Deb, M.; Rai, M.; Rai, J. Inkjet-printed paper-based colorimetric sensor coupled with smartphone for determination of mercury (Hg^{2+}). *J. Hazard. Mater.* **2021**, *414*, 125440. [\[CrossRef\]](#) [\[PubMed\]](#)
35. Liu, S.; Zhao, J.; Wu, J.; Wang, L.; Yao, C.; Hu, J.; Zhang, H. A microfluidic paper-based fluorescent sensor integrated with a smartphone platform for rapid on-site detection of omethoate pesticide. *Food Chem.* **2025**, *463*, 141205. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Fan, K.; Liu, W.; Miao, Y.; Li, Z.; Liu, G. Engineering Strategies for Advancing Optical Signal Outputs in Smartphone-Enabled Point-of-Care Diagnostics. *Adv. Intell. Syst.* **2023**, *5*, 2200285. [\[CrossRef\]](#)
37. Sukumaran, A.; Thomas, T.; Thomas, R.; Thomas, R.; Paul, J.; Vasudevan, D. Development and Troubleshooting in Lateral Flow Immunochromatography Assays. *Indian J. Clin. Biochem.* **2020**, *36*, 208–212. [\[CrossRef\]](#)
38. Zhang, X.; Chen, S.; Jin, S.; Zhang, Y.; Chen, X.; Zhang, Z.; Shu, Q. Naphthalene based lab-on-a-molecule for fluorimetric and colorimetric sensing of F^- and CN^- and nitroaromatic explosives. *Sens. Actuators B* **2017**, *242*, 994–998. [\[CrossRef\]](#)
39. Adhikari, S.; Noh, D.; Kim, M.; Ahn, D.; Jang, Y.; Oh, E.; Lee, D. Vapor phase detection of explosives by surface enhanced Raman scattering under ambient conditions with metal nanogap structures. *Spectrochim. Acta Part A* **2024**, *311*, 123996. [\[CrossRef\]](#)
40. Popa, D.; Udrea, F. Towards Integrated Mid-Infrared Gas Sensors. *Sensors* **2019**, *19*, 2076. [\[CrossRef\]](#)
41. Hodgkinson, J.; Tatam, R. Optical gas sensing: A review. *Meas. Sci. Technol.* **2012**, *24*, 012004. [\[CrossRef\]](#)
42. Shi, J.; Jiang, Y.; Duan, Z.; Li, J.; Yuan, Z.; Tai, H. Designing an Optical Gas Chamber with Stepped Structure for Non-Dispersive Infrared Methane Gas Sensor. *Sens. Actuators A* **2024**, *367*, 115052. [\[CrossRef\]](#)

43. Andersen, P.; Williford, C.; Birks, J. Miniature Personal Ozone Monitor Based on UV Absorbance. *Anal. Chem.* **2010**, *82*, 7924–7928. [[CrossRef](#)] [[PubMed](#)]
44. Gaynullin, B.; Hummelgard, C.; Rodjegard, H.; Mattsson, C.; Thungstrom, G. Environmental monitoring of methane utilizing multispectral NDIR gas sensing for compensation of spectral impact from water vapor in air. In Proceedings of the 2022 IEEE Sensors, Dallas, TX, USA, 30 October–2 November 2022; pp. 1–4. [[CrossRef](#)]
45. Gu, M.; Chen, J.; Zhang, Y.; Tan, T.; Wang, G.; Liu, K.; Gao, X.; Mei, J. Portable TDLAS Sensor for Online Monitoring of CO₂ and H₂O Using a Miniaturized Multi-Pass Cell. *Sensors* **2023**, *23*, 2072. [[CrossRef](#)] [[PubMed](#)]
46. Smith, B.J.; John, G.; Christensen, L.E.; Chen, Y. Fugitive Methane Leak Detection Using sUAS and Miniature Laser Spectrometer Payload: System, Application and Groundtruthing Tests. In Proceedings of the 2017 International Conference on Unmanned Aircraft Systems (ICUAS), Miami, FL, USA, 13–16 June 2017; pp. 369–374. [[CrossRef](#)]
47. Yang, S.; Talbot, R.; Frish, M.; Golston, L.; Aubut, N.; Zondlo, M.; Gretencord, C.; McSpirt, J. Natural Gas Fugitive Leak Detection Using an Unmanned Aerial Vehicle: Measurement System Description and Mass Balance Approach. *Atmosphere* **2018**, *9*, 383. [[CrossRef](#)]
48. Hansemann, C.; Bonarens, M.; Emmert, J.; Daun, K.; Wagner, S. Towards a spatially resolved, single-ended TDLAS system for characterizing the distribution of gaseous species. *Sci. Rep.* **2024**, *14*, 11708. [[CrossRef](#)]
49. Yang, J.; Swager, T. Fluorescent Porous Polymer Films as TNT Chemosensors: Electronic and Structural Effects. *J. Am. Chem. Soc.* **1998**, *120*, 11864–11873. [[CrossRef](#)]
50. Zhao, Y.; Miao, K.; Zhu, Z.; Fan, L. Fluorescence Quenching of a Conjugated Polymer by Synergistic Amine-Carboxylic Acid and π - π Interactions for Selective Detection of Aromatic Amines in Aqueous Solution. *ACS Sens.* **2017**, *2*, 842–847. [[CrossRef](#)]
51. Anjali Devi, J.; Madanan Anju, S.; Lekha, G.; Aparna, R.; George, S. Luminescent carbon dots versus quantum dots and gold nanoclusters as sensors. *Nanoscale Horiz.* **2024**, *9*, 1683–1702. [[CrossRef](#)]
52. Nimisha, O.; Pradeesh, K.; Reena Mary, A. Fluorescence quenching of fluorescein dye using silver nanoparticles. *Mater. Today Proc.* **2023**. [[CrossRef](#)]
53. Adhikari, S.; Ampadu, E.; Kim, M.; Noh, D.; Oh, E.; Lee, D. Detection of Explosives by SERS Platform Using Metal Nanogap Substrates. *Sensors* **2021**, *21*, 5567. [[CrossRef](#)]
54. Pilot, R.; Signorini, R.; Durante, C.; Orian, L.; Bhamidipati, M.; Fabris, L. A Review on Surface-Enhanced Raman Scattering. *Biosensors* **2019**, *9*, 57. [[CrossRef](#)]
55. Adhikari, S.; Joshi, R.; Joshi, R.; Kim, M.; Jang, Y.; Tufa, L.; Gicha, B.; Lee, J.; Lee, D.; Cho, B. Rapid and ultrasensitive detection of thiram and carbaryl pesticide residues in fruit juices using SERS coupled with the chemometrics technique. *Food Chem.* **2024**, *457*, 140486. [[CrossRef](#)] [[PubMed](#)]
56. Yang, Y.; Chen, X.; Ai, B.; Zhao, Y. The impact of analyte size on SERS enhancement location, enhancement factor, excitation wavelength, and spectrum. *Sens. Diagn.* **2024**, *3*, 668–676. [[CrossRef](#)]
57. Dodo, K.; Fujita, K.; Sodeoka, M. Raman Spectroscopy for Chemical Biology Research. *J. Am. Chem. Soc.* **2022**, *144*, 19651–19667. [[CrossRef](#)] [[PubMed](#)]
58. Zeng, F.; Mou, T.; Zhang, C.; Huang, X.; Wang, B.; Ma, X.; Guo, J. Paper-based SERS analysis with smartphones as Raman spectral analyzers. *Analyst* **2019**, *144*, 137–142. [[CrossRef](#)]
59. Kant, T.; Shrivastava, K.; Tejawani, A.; Tandey, K.; Sharma, A.; Gupta, S. Progress in the design of portable colorimetric chemical sensing devices. *Nanoscale* **2023**, *15*, 19016–19038. [[CrossRef](#)]
60. Shahvar, A.; Shamsaei, D.; Saraji, M. A portable smartphone-based colorimetric sensor for rapid determination of water content in ethanol. *Measurement* **2020**, *150*, 107068. [[CrossRef](#)]
61. Dutta, S.; Saikia, G.; Sarma, D.; Gupta, K.; Das, P.; Nath, P. Protein, enzyme and carbohydrate quantification using smartphone through colorimetric digitization technique. *J. Biophotonics* **2016**, *10*, 623–633. [[CrossRef](#)]
62. Shrivastava, K.; Monisha; Kant, T.; Karbhal, I.; Kurrey, R.; Sahu, B.; Sinha, D.; Patra, G.; Deb, M.; Pervez, S. Smartphone coupled with paper-based chemical sensor for on-site determination of iron(III) in environmental and biological samples. *Anal. Bioanal. Chem.* **2020**, *412*, 1573–1583. [[CrossRef](#)]
63. Celikbas, E.; Ceylan, A.; Timur, S. Paper-based colorimetric spot test utilizing smartphone sensing for detection of biomarkers. *Talanta* **2020**, *208*, 120446. [[CrossRef](#)]
64. Bao, X.; Jiang, S.; Wang, Y.; Yu, M.; Han, J. A remote computing based point-of-care colorimetric detection system with a smartphone under complex ambient light conditions. *Analyst* **2018**, *143*, 1387–1395. [[CrossRef](#)]
65. Montaña-Priede, J.; Sanromán-Iglesias, M.; Zabala, N.; Grzelczak, M.; Aizpuru, J. Robust Rules for Optimal Colorimetric Sensing Based on Gold Nanoparticle Aggregation. *ACS Sens.* **2023**, *8*, 1827–1834. [[CrossRef](#)] [[PubMed](#)]
66. Shao, X.; Yang, D.; Wang, M.; Yue, Q. A colorimetric detection of Hg²⁺ based on gold nanoparticles synthesized oxidized N-methylpyrrolidone as a reducing agent. *Sci. Rep.* **2023**, *13*, 22208. [[CrossRef](#)] [[PubMed](#)]

67. Ki, J.; Kwon, I.; Lee, J.; Lim, J.; Jang, S.; Son, S.; Seo, S.; Oh, S.; Kang, T.; Jung, J.; et al. A portable smartphone-based colorimetric sensor that utilizes dual amplification for the on-site detection of airborne bacteria. *J. Hazard. Mater.* **2023**, *460*, 132398. [\[CrossRef\]](#)
68. Bioucas-Dias, J.; Plaza, A.; Camps-Valls, G.; Scheunders, P.; Nasrabadi, N.; Chanussot, J. Hyperspectral Remote Sensing Data Analysis and Future Challenges. *IEEE Geosci. Remote Sens. Mag.* **2013**, *1*, 6–36. [\[CrossRef\]](#)
69. Chen, Y.; Li, M.; Yan, W.; Zhuang, X.; Ng, K.W.; Cheng, X. Sensitive and Low-Power Metal Oxide Gas Sensors with a Low-Cost Microelectromechanical Heater. *ACS Omega* **2021**, *6*, 1216–1222. [\[CrossRef\]](#)
70. Marikutsa, A.; Rumyantseva, M.; Konstantinova, E.; Gaskov, A. The Key Role of Active Sites in the Development of Selective Metal Oxide Sensor Materials. *Sensors* **2021**, *21*, 2554. [\[CrossRef\]](#)
71. Marco, S.; Gutierrez-Galvez, A. Signal and Data Processing for Machine Olfaction and Chemical Sensing: A Review. *IEEE Sens. J.* **2012**, *12*, 3189–3214. [\[CrossRef\]](#)
72. Gutierrez-Osuna, R.; Gutierrez-Galvez, A.; Powar, N. Transient response analysis for temperature-modulated chemoresistors. *Sens. Actuators B* **2003**, *93*, 57–66. [\[CrossRef\]](#)
73. Lee, A. Temperature modulation in semiconductor gas sensing. *Sens. Actuators B* **1999**, *60*, 35–42. [\[CrossRef\]](#)
74. Kanan, S.; El-Kadri, O.; Abu-Yousef, I.; Kanan, M. Semiconducting Metal Oxide Based Sensors for Selective Gas Pollutant Detection. *Sensors* **2009**, *9*, 8158–8196. [\[CrossRef\]](#)
75. Matsubara, I.; Hosono, K.; Murayama, N.; Shin, W.; Izu, N. Organically hybridized SnO₂ gas sensors. *Sens. Actuators B* **2005**, *108*, 143–147. [\[CrossRef\]](#)
76. Woo, H.; Na, C.; Lee, J. Design of Highly Selective Gas Sensors via Physicochemical Modification of Oxide Nanowires: Overview. *Sensors* **2016**, *16*, 1531. [\[CrossRef\]](#) [\[PubMed\]](#)
77. Wang, C.; Yin, L.; Zhang, L.; Xiang, D.; Gao, R. Metal Oxide Gas Sensors: Sensitivity and Influencing Factors. *Sensors* **2010**, *10*, 2088–2106. [\[CrossRef\]](#) [\[PubMed\]](#)
78. Korotcenkov, G. Gas response control through structural and chemical modification of metal oxide films: State of the art and approaches. *Sens. Actuators B* **2005**, *107*, 209–232. [\[CrossRef\]](#)
79. Degler, D.; Weimar, U.; Barsan, N. Current Understanding of the Fundamental Mechanisms of Doped and Loaded Semiconducting Metal-Oxide-Based Gas Sensing Materials. *ACS Sens.* **2019**, *4*, 2228–2249. [\[CrossRef\]](#)
80. Korotcenkov, G.; Cho, B. Metal oxide composites in conductometric gas sensors: Achievements and challenges. *Sens. Actuators B* **2017**, *244*, 182–210. [\[CrossRef\]](#)
81. Jeong, S.; Kim, J.; Lee, J. Rational Design of Semiconductor-Based Chemiresistors and their Libraries for Next-Generation Artificial Olfaction. *Adv. Mater.* **2020**, *32*, 2002075. [\[CrossRef\]](#)
82. Yoon, J.; Kim, H.; Kim, I.; Lee, J. Electronic sensitization of the response to C₂H₅OH of p-type NiO nanofibers by Fe doping. *Nanotechnology* **2013**, *24*, 444005. [\[CrossRef\]](#)
83. Kim, H.; Yoon, J.; Choi, K.; Jang, H.; Umar, A.; Lee, J. Ultrasensitive and sensitive detection of xylene and toluene for monitoring indoor air pollution using Cr-doped NiO hierarchical nanostructures. *Nanoscale* **2013**, *5*, 7066. [\[CrossRef\]](#)
84. Kim, B.; Yoon, J.; Kim, J.; Kang, Y.; Lee, J. Dual Role of Multiroom-Structured Sn-Doped NiO Microspheres for Ultrasensitive and Highly Selective Detection of Xylene. *ACS Appl. Mater. Interfaces* **2018**, *10*, 16605–16612. [\[CrossRef\]](#)
85. Kim, K.; Jeong, S.; Kim, T.; Kang, Y.; Lee, J. Methylbenzene sensors using Ti-doped NiO multiroom spheres: Versatile tunability on selectivity, response, sensitivity, and detection limit. *Sens. Actuators B* **2020**, *308*, 127730. [\[CrossRef\]](#)
86. Kim, T.; Jeong, S.; Moon, Y.; Lee, J. Dual-mode gas sensor for ultrasensitive and highly selective detection of xylene and toluene using Nb-doped NiO hollow spheres. *Sens. Actuators B* **2019**, *301*, 127140. [\[CrossRef\]](#)
87. Xia, Y.; Li, R.; Chen, R.; Wang, J.; Xiang, L. 3D Architected Graphene/Metal Oxide Hybrids for Gas Sensors: A Review. *Sensors* **2018**, *18*, 1456. [\[CrossRef\]](#) [\[PubMed\]](#)
88. Ilnicka, A.; Lukaszewicz, J. Graphene-Based Hydrogen Gas Sensors: A Review. *Processes* **2020**, *8*, 633. [\[CrossRef\]](#)
89. Albert, K.; Lewis, N.; Schauer, C.; Sotzing, G.; Stitzel, S.; Vaid, T.; Walt, D. Cross-Reactive Chemical Sensor Arrays. *Chem. Rev.* **2000**, *100*, 2595–2626. [\[CrossRef\]](#)
90. Sberveglieri, G. Classical and novel techniques for the preparation of SnO₂ thin-film gas sensors. *Sens. Actuators B* **1992**, *6*, 239–247. [\[CrossRef\]](#)
91. Monroy, J.; González-Jiménez, J.; Blanco, J. Overcoming the Slow Recovery of MOX Gas Sensors through a System Modeling Approach. *Sensors* **2012**, *12*, 13664–13680. [\[CrossRef\]](#)
92. Gonzalez-Jimenez, J.; Monroy, J.; Blanco, J. The Multi-Chamber Electronic Nose—An Improved Olfaction Sensor for Mobile Robotics. *Sensors* **2011**, *11*, 6145–6164. [\[CrossRef\]](#)
93. Serafini, M.; Mariani, F.; Gualandi, I.; Decataldo, F.; Possanzini, L.; Tessarolo, M.; Fraboni, B.; Tonelli, D.; Scavetta, E. A Wearable Electrochemical Gas Sensor for Ammonia Detection. *Sensors* **2021**, *21*, 7905. [\[CrossRef\]](#)
94. Zhang, Y.; Cheng, D.; Wu, Z.; Li, F.; Fang, F.; Zhan, Z. Fumed SiO₂-H₂SO₄-PVA Gel Electrolyte CO Electrochemical Gas Sensor. *Chemosensors* **2020**, *8*, 109. [\[CrossRef\]](#)

95. Song, S.; Wang, L.; Li, J.; Fan, C.; Zhao, J. Aptamer-based biosensors. *TrAC Trends Anal. Chem.* **2008**, *27*, 108–117. [\[CrossRef\]](#)
96. Waifalkar, P.; Noh, D.; Derashri, P.; Barage, S.; Oh, E. Role of Estradiol Hormone in Human Life and Electrochemical Aptasensing of 17 β -Estradiol: A Review. *Biosensors* **2022**, *12*, 1117. [\[CrossRef\]](#) [\[PubMed\]](#)
97. Zamay, G.; Zamay, T.; Kolovskii, V.; Shabanov, A.; Glazyrin, Y.; Veprintsev, D.; Krat, A.; Zamay, S.; Kolovskaya, O.; Gargaun, A.; et al. Electrochemical aptasensor for lung cancer-related protein detection in crude blood plasma samples. *Sci. Rep.* **2016**, *6*, 34350. [\[CrossRef\]](#) [\[PubMed\]](#)
98. Wu, J.; Liu, H.; Chen, W.; Ma, B.; Ju, H. Device integration of electrochemical biosensors. *Nat. Rev. Bioeng.* **2023**, *1*, 346–360. [\[CrossRef\]](#)
99. Golston, L.; Aubut, N.; Frish, M.; Yang, S.; Talbot, R.; Gretencord, C.; McSpirt, J.; Zondlo, M. Natural Gas Fugitive Leak Detection Using an Unmanned Aerial Vehicle: Localization and Quantification of Emission Rate. *Atmosphere* **2018**, *9*, 333. [\[CrossRef\]](#)
100. Martinez, B.; Miller, T.; Yalin, A. Cavity Ring-Down Methane Sensor for Small Unmanned Aerial Systems. *Sensors* **2020**, *20*, 454. [\[CrossRef\]](#)
101. Barchyn, T.; Hugenholtz, C.; Fox, T. Plume detection modeling of a drone-based natural gas leak detection system. *Elem. Sci. Anth.* **2019**, *7*, 41. [\[CrossRef\]](#)
102. Emran, B.; Tannant, D.; Najjaran, H. Low-Altitude Aerial Methane Concentration Mapping. *Remote Sens.* **2017**, *9*, 823. [\[CrossRef\]](#)
103. Bretschneider, T.R.; Shetti, K. UAV-based gas pipeline leak detection. In Proceedings of the Asian Conference on Remote Sensing, NayPyi Taw, Myanmar, 27–31 October 2014.
104. Tannant, D.; Zheng, W.; Smith, K.; Cahill, A. *Evaluation of a Drone and Laser-Based Methane Sensor for Detection of a Surface Release of Methane*; University of British Columbia: Vancouver, BC, Canada, 2018.
105. Tassielli, G.; Cananà, L.; Spalatro, M. Detection of Methane Leaks via a Drone-Based System for Sustainable Landfills and Oil and Gas Facilities: Effect of Different Variables on the Background-Noise Measurement. *Sustainability* **2024**, *16*, 7748. [\[CrossRef\]](#)
106. Marturano, F.; Martellucci, L.; Chierici, A.; Malizia, A.; Giovanni, D.D.; d’Errico, F.; Gaudio, P.; Ciparisse, J.-F. Numerical Fluid Dynamics Simulation for Drones’ Chemical Detection. *Drones* **2021**, *5*, 69. [\[CrossRef\]](#)
107. Do, S.; Lee, M.; Kim, J.-S. The Effect of a Flow Field on Chemical Detection Performance of Quadrotor Drone. *Sensors* **2020**, *20*, 3262. [\[CrossRef\]](#) [\[PubMed\]](#)
108. Chae, S.; Lee, S.; Hwang, S.; Jeong, S.; Kim, J. Effects of Rotor–Rotor Interaction for a Small Tandem Rotor Operating in a Crosswind. *Phys. Fluids* **2024**, *36*, 065147. [\[CrossRef\]](#)
109. Szczurek, A.; Gonstał, D.; Maciejewska, M. The Gas Sensing Drone with the Lowered and Lifted Measurement Platform. *Sensors* **2023**, *23*, 1253. [\[CrossRef\]](#) [\[PubMed\]](#)
110. Neumann, P.; Kohlhoff, H.; Hullmann, D.; Lilienthal, A.; Kluge, M. Bringing Mobile Robot Olfaction to the next dimension—UAV-based remote sensing of gas clouds and source localization. In Proceedings of the 2017 IEEE International Conference on Robotics and Automation (ICRA), Singapore, 29 May–3 June 2017; pp. 3910–3916. [\[CrossRef\]](#)
111. Neumann, P.; Kohlhoff, H.; Hüllmann, D.; Krentel, D.; Kluge, M.; Dzierliński, M.; Lilienthal, A.; Bartholmai, M. Aerial-based gas tomography—From single beams to complex gas distributions. *Eur. J. Remote Sens.* **2019**, *52*, 2–16. [\[CrossRef\]](#)
112. Gardner, J.; Bartlett, P. A brief history of electronic noses. *Sens. Actuators B* **1994**, *18*, 210–211. [\[CrossRef\]](#)
113. Wojnowski, W.; Dymerski, T.; Gębicki, J.; Namieśnik, J. Electronic Noses in Medical Diagnostics. *Curr. Med. Chem.* **2019**, *26*, 197–215. [\[CrossRef\]](#)
114. Loutfi, A.; Coradeschi, S.; Mani, G.; Shankar, P.; Rayappan, J. Electronic noses for food quality: A review. *J. Food Eng.* **2015**, *144*, 103–111. [\[CrossRef\]](#)
115. Kiani, S.; Minaei, S.; Ghasemi-Varnamkhasti, M. Application of electronic nose systems for assessing quality of medicinal and aromatic plant products: A review. *J. Appl. Res. Med. Aromat. Plants* **2016**, *3*, 1–9. [\[CrossRef\]](#)
116. Bax, C.; Sironi, S.; Capelli, L. How Can Odors Be Measured? An Overview of Methods and Their Applications. *Atmosphere* **2020**, *11*, 92. [\[CrossRef\]](#)
117. Burgués, J.; Doñate, S.; Esclapez, M.; Saúco, L.; Marco, S. Characterization of odour emissions in a wastewater treatment plant using a drone-based chemical sensor system. *Sci. Total Environ.* **2022**, *846*, 157290. [\[CrossRef\]](#)
118. Kang, M.; Cho, I.; Park, J.; Jeong, J.; Lee, K.; Lee, B.; Del Orbe Henriquez, D.; Yoon, K.; Park, I. High Accuracy Real-Time Multi-Gas Identification by a Batch-Uniform Gas Sensor Array and Deep Learning Algorithm. *ACS Sens.* **2022**, *7*, 430–440. [\[CrossRef\]](#) [\[PubMed\]](#)
119. Lee, K.; Cho, I.; Kang, M.; Jeong, J.; Choi, M.; Woo, K.; Yoon, K.; Cho, Y.; Park, I. Ultra-Low-Power E-Nose System Based on Multi-Micro-LED-Integrated, Nanostructured Gas Sensors and Deep Learning. *ACS Nano* **2022**, *17*, 539–551. [\[CrossRef\]](#) [\[PubMed\]](#)
120. Wang, T.; Zhang, H.; Wu, Y.; Jiang, W.; Chen, X.; Zeng, M.; Yang, J.; Su, Y.; Hu, N.; Yang, Z. Target discrimination, concentration prediction, and status judgment of electronic nose system based on large-scale measurement and multi-task deep learning. *Sens. Actuators B* **2022**, *351*, 130915. [\[CrossRef\]](#)
121. Mei, H.; Peng, J.; Wang, T.; Zhou, T.; Zhao, H.; Zhang, T.; Yang, Z. Overcoming the Limits of Cross-Sensitivity: Pattern Recognition Methods for Chemiresistive Gas Sensor Array. *Nano Micro Lett.* **2024**, *16*, 269. [\[CrossRef\]](#)

122. Burgues, J.; Valdez, L.; Marco, S. High-bandwidth e-nose for rapid tracking of turbulent plumes. In Proceedings of the 2019 IEEE International Symposium on Olfaction and Electronic Nose (ISOEN), Fukuoka, Japan, 26–29 May 2019; pp. 1–3. [\[CrossRef\]](#)
123. Sitar, A.; Scattolo, E.; Valt, M.; Bagolini, A.; Tosato, P.; Gaiardo, A. Sensing Material Temperature Effect on the Multiple Gas Sensor Sensing Response. *Proceedings* **2024**, *97*, 130. [\[CrossRef\]](#)
124. Ayaz, U.; Topuk, S. Performance Analysis of Relative Humidity Factor and CH₄ Concentration Measurements for NDIR Gas Sensor. In Proceedings of the 2021 13th International Conference on Electrical and Electronics Engineering (ELECO), Bursa, Turkey, 25–27 November 2021; Volume 28, pp. 206–210. [\[CrossRef\]](#)
125. Gorokh, G.; Taratyn, I.; Fiadosenka, U.; Reutskaya, O.; Lozovenko, A. Heater Topology Influence on the Functional Characteristics of Thin-Film Gas Sensors Made by MEMS-Silicon Technology. *Chemosensors* **2023**, *11*, 443. [\[CrossRef\]](#)
126. Pitaloka, D.; Ikhsani, R.; Naba, A.; Sakti, S. Thermoelectric-based temperature control for rapid heating and cooling. *IOP Conf. Ser. Mater. Sci. Eng.* **2019**, *546*, 032026. [\[CrossRef\]](#)
127. Majhi, S.; Mirzaei, A.; Kim, H.; Kim, S.; Kim, T. Recent advances in energy-saving chemiresistive gas sensors: A review. *Nano Energy* **2021**, *79*, 105369. [\[CrossRef\]](#)
128. Son, D.; Hung, C.; Thi Thanh Le, D.; Thi Xuan, C.; Van Duy, N.; Dich, N.; Nguyen, H.; Van Hieu, N.; Hoa, N. A novel design and fabrication of self-heated In₂O₃ nanowire gas sensor on glass for ethanol detection. *Sens. Actuators A* **2022**, *345*, 113769. [\[CrossRef\]](#)
129. Samad, A.; Obando Nuñez, D.; Solis Castillo, G.; Laquai, B.; Vogt, U. Effect of Relative Humidity and Air Temperature on the Results Obtained from Low-Cost Gas Sensors for Ambient Air Quality Measurements. *Sensors* **2020**, *20*, 5175. [\[CrossRef\]](#)
130. Annanouch, F.; Bouchet, G.; Perrier, P.; Morati, N.; Reynard-Carette, C.; Aguir, K.; Martini-Laithier, V.; Bendahan, M. Hydrodynamic evaluation of gas testing chamber: Simulation, experiment. *Sens. Actuators B* **2019**, *290*, 598–606. [\[CrossRef\]](#)
131. Mahdavi, H.; Rahbarpour, S.; Goldoust, R.; Hosseini-Golgoos, S.; Jamaati, H. Investigating Simultaneous Effects of Flow Rate and Chamber Structure on the Performance of Metal Oxide Gas Sensors. *IEEE Sens. J.* **2021**, *21*, 21612–21621. [\[CrossRef\]](#)
132. Robbiani, S.; Lotesoriere, B.; Dellacà, R.; Capelli, L. Physical Confounding Factors Affecting Gas Sensors Response: A Review on Effects and Compensation Strategies for Electronic Nose Applications. *Chemosensors* **2023**, *11*, 514. [\[CrossRef\]](#)
133. Liu, C.; Duan, Z.; Zhang, B.; Zhao, Y.; Yuan, Z.; Zhang, Y.; Wu, Y.; Jiang, Y.; Tai, H. Local Gaussian process regression with small sample data for temperature and humidity compensation of polyaniline-cerium dioxide NH₃ sensor. *Sens. Actuators B* **2023**, *378*, 133113. [\[CrossRef\]](#)
134. Papaconstantinou, R.; Demosthenous, M.; Bezantakos, S.; Hadjigeorgiou, N.; Costi, M.; Stylianou, M.; Symeou, E.; Savvides, C.; Biskos, G. Field evaluation of low-cost electrochemical air quality gas sensors under extreme temperature and relative humidity conditions. *Atmos. Meas. Tech.* **2023**, *16*, 3313–3329. [\[CrossRef\]](#)
135. Müller, G.; Sberveglieri, G. Origin of Baseline Drift in Metal Oxide Gas Sensors: Effects of Bulk Equilibration. *Chemosensors* **2022**, *10*, 171. [\[CrossRef\]](#)
136. Nelli, P.; Faglia, G.; Sberveglieri, G.; Cereda, E.; Gabetta, G.; Dieguez, A.; Romano-Rodriguez, A.; Morante, J. The aging effect on SnO₂–Au thin film sensors: Electrical and structural characterization. *Thin Solid Film.* **2000**, *371*, 249–253. [\[CrossRef\]](#)
137. Koziel, S.; Pietrenko-Dabrowska, A.; Wojcikowski, M.; Pankiewicz, B. Machine-learning-based precise cost-efficient NO₂ sensor calibration by means of time series matching and global data pre-processing. *Eng. Sci. Technol. Int. J.* **2024**, *54*, 101729. [\[CrossRef\]](#)
138. Kwon, S.; Park, J.; Jang, H.; Nam, H.; Chang, D. A Sensor Drift Compensation Method with a Masked Autoencoder Module. *Appl. Sci.* **2024**, *14*, 2604. [\[CrossRef\]](#)
139. Vergara, A.; Vembu, S.; Ayhan, T.; Ryan, M.; Homer, M.; Huerta, R. Chemical gas sensor drift compensation using classifier ensembles. *Sens. Actuators B* **2012**, *166*, 320–329. [\[CrossRef\]](#)
140. Llobet, E.; Brezmes, J.; Ionescu, R.; Vilanova, X.; Al-Khalifa, S.; Gardner, J.; Bàrsan, N.; Correig, X. Wavelet transform and fuzzy ARTMAP-based pattern recognition for fast gas identification using a micro-hotplate gas sensor. *Sens. Actuators B* **2002**, *83*, 238–244. [\[CrossRef\]](#)
141. Fan, Y.; Chou, T.; Chiu, S.; Tang, K. Gas Identification Algorithm Based on Dynamic Response Analysis of Metal Oxide Sensors Under Temperature Modulation. *IEEE Access* **2024**, *12*, 87900–87908. [\[CrossRef\]](#)
142. Cho, I.; Lee, K.; Sim, Y.; Jeong, J.; Cho, M.; Jung, H.; Kang, M.; Cho, Y.; Ha, S.; Yoon, K.; et al. Deep-learning-based gas identification by time-variant illumination of a single micro-LED-embedded gas sensor. *Light Sci. Appl.* **2023**, *12*, 95. [\[CrossRef\]](#) [\[PubMed\]](#)
143. Potyrailo, R.; Go, S.; Sexton, D.; Li, X.; Alkadi, N.; Kolmakov, A.; Amm, B.; St-Pierre, R.; Scherer, B.; Nayeri, M.; et al. Extraordinary performance of semiconducting metal oxide gas sensors using dielectric excitation. *Nat. Electron.* **2020**, *3*, 280–289. [\[CrossRef\]](#)
144. Rudnitskaya, A. Calibration Update and Drift Correction for Electronic Noses and Tongues. *Front. Chem.* **2018**, *6*, 433. [\[CrossRef\]](#)
145. Chen, X.; Huang, J. Odor source localization algorithms on mobile robots: A review and future outlook. *Robot. Auton. Syst.* **2019**, *112*, 123–136. [\[CrossRef\]](#)
146. Kowadlo, G.; Russell, R. Robot Odor Localization: A Taxonomy and Survey. *Int. J. Robot. Res.* **2008**, *27*, 869–894. [\[CrossRef\]](#)
147. Park, M.; An, S.; Seo, J.; Oh, H. Autonomous Source Search for UAVs Using Gaussian Mixture Model-Based Infotaxis: Algorithm and Flight Experiments. *IEEE Trans. Aerosp. Electron. Syst.* **2021**, *57*, 4238–4254. [\[CrossRef\]](#)

148. Ma, D.; Mao, W.; Tan, W.; Gao, J.; Zhang, Z.; Xie, Y. Emission Source Tracing Based on Bionic Algorithm Mobile Sensors with Artificial Olfactory System. *Robotica* **2021**, *40*, 976–996. [\[CrossRef\]](#)
149. Burgués, J. Signal Processing and Machine Learning for Gas Sensors: Gas Source Localization with a Nano-Drone. Ph.D. Thesis, University of Barcelona, Barcelona, Spain, 2019.
150. Shu, L.; Mukherjee, M.; Xu, X.; Wang, K.; Wu, X. A Survey on Gas Leakage Source Detection and Boundary Tracking with Wireless Sensor Networks. *IEEE Access* **2016**, *4*, 1700–1715. [\[CrossRef\]](#)
151. Shu, L.; Mukherjee, M.; Wu, X. Toxic Gas Boundary Area Detection in Large-Scale Petrochemical Plants with Industrial Wireless Sensor Networks. *IEEE Commun. Mag.* **2016**, *54*, 22–28. [\[CrossRef\]](#)
152. Shu, L.; Chen, Y.; Sun, Z.; Tong, F.; Mukherjee, M. Detecting the Dangerous Area of Toxic Gases with Wireless Sensor Networks. *IEEE Trans. Emerg. Top. Comput.* **2020**, *8*, 137–147. [\[CrossRef\]](#)
153. Liu, L.; Han, G.; Xu, Z.; Jiang, J.; Shu, L.; Martinez-Garcia, M. Boundary Tracking of Continuous Objects Based on Binary Tree Structured SVM for Industrial Wireless Sensor Networks. *IEEE Trans. Mob. Comput.* **2022**, *21*, 849–861. [\[CrossRef\]](#)
154. Han, G.; Shen, J.; Liu, L.; Qian, A.; Shu, L. TGM-COT: Energy-Efficient Continuous Object Tracking Scheme with Two-Layer Grid Model in Wireless Sensor Networks. *Pers. Ubiquitous Comput.* **2016**, *20*, 349–359. [\[CrossRef\]](#)
155. Imran, S.; Ko, Y.-B. A Continuous Object Boundary Detection and Tracking Scheme for Failure-Prone Sensor Networks. *Sensors* **2017**, *17*, 361. [\[CrossRef\]](#)
156. Han, G.; Shen, J.; Liu, L.; Shu, L. BRTCO: A Novel Boundary Recognition and Tracking Algorithm for Continuous Objects in Wireless Sensor Networks. *IEEE Syst. J.* **2018**, *12*, 2056–2065. [\[CrossRef\]](#)
157. Ma, D.; Gao, J.; Zhang, Z.; Zhao, H. Gas Recognition Method Based on the Deep Learning Model of Sensor Array Response Map. *Sens. Actuators B* **2021**, *330*, 129349. [\[CrossRef\]](#)
158. Viet, N.; Phuoc, P.; Thong, L.; Chien, N.; Van Hieu, N. A comparative study of machine learning models for identifying noxious gases through thermal fingerprint measurements and MOS sensors. *Sens. Actuators A* **2024**, *375*, 115510. [\[CrossRef\]](#)
159. Khan, M.; Thomson, B.; Debnath, R.; Motayed, A.; Rao, M. Nanowire-Based Sensor Array for Detection of Cross-Sensitive Gases Using PCA and Machine Learning Algorithms. *IEEE Sens. J.* **2020**, *20*, 6020–6028. [\[CrossRef\]](#)
160. Vergara, A.; Calavia, R.; Vázquez, R.; Mozalev, A.; Abdelghani, A.; Huerta, R.; Hines, E.; Llobet, E. Multifrequency Interrogation of Nanostructured Gas Sensor Arrays: A Tool for Analyzing Response Kinetics. *Anal. Chem.* **2012**, *84*, 7502–7510. [\[CrossRef\]](#)
161. Giordano, G.; Ferreira, L.; Bezerra, Í.; Barbosa, J.; Costa, J.; Pimentel, G.; Lima, R. Machine learning toward high-performance electrochemical sensors. *Anal. Bioanal. Chem.* **2023**, *415*, 3683–3692. [\[CrossRef\]](#) [\[PubMed\]](#)
162. Cui, F.; Yue, Y.; Zhang, Y.; Zhang, Z.; Zhou, H. Advancing Biosensors with Machine Learning. *ACS Sens.* **2020**, *5*, 3346–3364. [\[CrossRef\]](#) [\[PubMed\]](#)
163. Xu, Y.; Rao, Z.; Liu, Z.; Zheng, W.; Zhou, Y.; Lu, N.; Yang, Y. Improving the Selectivity in Electrochemical Detection of Chloramphenicol Against Metronidazole With Machine Learning. *IEEE Sens. J.* **2023**, *23*, 17883–17890. [\[CrossRef\]](#)
164. Kang, M.; Kim, D.; Kim, J.; Kim, N.; Lee, S. Strategies to Enrich Electrochemical Sensing Data with Analytical Relevance for Machine Learning Applications: A Focused Review. *Sensors* **2024**, *24*, 3855. [\[CrossRef\]](#)
165. Aliev, T.; Belyaev, V.; Pomytkina, A.; Nesterov, P.; Shityakov, S.; Sadovnichii, R.; Novikov, A.; Orlova, O.; Masalovich, M.; Skorb, E. Electrochemical Sensor to Detect Antibiotics in Milk Based on Machine Learning Algorithms. *ACS Appl. Mater. Interfaces* **2023**, *15*, 52010–52020. [\[CrossRef\]](#)
166. Biscaglia, F.; Caroppo, A.; Prontera, C.; Sciurti, E.; Signore, M.; Kuznetsova, I.; Leone, A.; Siciliano, P.; Francioso, L. A Comparison between Different Machine Learning Approaches Combined with Anodic Stripping Voltammetry for Copper Ions and pH Detection in Cell Culture Media. *Chemosensors* **2023**, *11*, 61. [\[CrossRef\]](#)
167. Huang, X.; Li, Y.; Witherspoon, E.; He, R.; Petruncio, G.; Paige, M.; Li, M.; Liu, T.; Amine, K.; Wang, Z.; et al. Species-Selective Detection of Volatile Organic Compounds by Ionic Liquid-Based Electrolyte Using Electrochemical Methods. *ACS Sens.* **2023**, *8*, 3389–3399. [\[CrossRef\]](#)
168. Wang, T.; Mei, Q.; Tao, Z.; Wu, H.; Zhao, M.; Wang, S.; Liu, Y. A smartphone-integrated ratiometric fluorescence sensing platform for visual and quantitative point-of-care testing of tetracycline. *Biosens. Bioelectron.* **2020**, *148*, 111791. [\[CrossRef\]](#)
169. Liang, C.; Liu, Y.; Niu, A.; Liu, C.; Li, J.; Ning, D. Smartphone-app based point-of-care testing for myocardial infarction biomarker cTnI using an autonomous capillary microfluidic chip with self-aligned on-chip focusing (SOF) lenses. *Lab Chip* **2019**, *19*, 1797–1807. [\[CrossRef\]](#)
170. Mousavizadegan, M.; Hosseini, M.; Sheikholeslami, M.; Hamidipناه, Y.; Reza Ganjali, M. Smartphone image analysis-based fluorescence detection of tetracycline using machine learning. *Food Chem.* **2023**, *403*, 134364. [\[CrossRef\]](#)
171. Mutlu, A.; Kılıç, V.; Özdemir, G.; Bayram, A.; Horzum, N.; Solmaz, M. Smartphone-based colorimetric detection via machine learning. *Analyst* **2017**, *142*, 2434–2441. [\[CrossRef\]](#) [\[PubMed\]](#)
172. Akkaynak, D.; Treibitz, T.; Xiao, B.; Gürkan, U.; Allen, J.; Demirci, U.; Hanlon, R. Use of commercial off-the-shelf digital cameras for scientific data acquisition and scene-specific color calibration. *J. Opt. Soc. Am. A* **2014**, *31*, 312. [\[CrossRef\]](#) [\[PubMed\]](#)

173. Jiang, C.; Guo, A.; Li, Y.; Wang, Y.; Sun, J.; Chen, Z.; Chen, X.; Ma, Q. Inspired by human olfactory system: Deep-learning-assisted portable chemo-responsive dye-based odor sensor array for the rapid sensing of shrimp and fish freshness. *Chem. Eng. J.* **2024**, *484*, 149283. [[CrossRef](#)]
174. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep Residual Learning for Image Recognition. *arXiv* **2015**. [[CrossRef](#)]

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