

NOSEwrist: Natural Olfactory Substitution and Extension wrist

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ABSTRACT

In this paper, we present a wearable augmentation device that ultimately aims to substitute and extend olfactory sensation. The device utilizes gas sensors mounted on the wrist, combined with a trained machine learning model, to discriminate liquids such as water, alcohol, fluid accelerant, and vinegar. The device aims to be useful in cases where the sense of taste and smell are compromised, such as sometimes occurring during a COVID-19 infection. The paper also discusses potential advancements for this technology to be utilized in a variety of ways, beyond just substituting a broken sense, and how it aligns with the vision of early HCI pioneer Douglas Engelbart, and the concept of Assistive Augmentation. The paper concludes that this technology, in combination with artificial intelligence, has the potential to enrich our physical experience and bring us closer to the idea of a "Cyber-Human" in the future.

CCS CONCEPTS

• **Human-centered computing** → Ubiquitous and mobile computing; • **Applied computing** → Health informatics.

KEYWORDS

Human Augmentation, Neural Networks, Olfactory Sensation, Smell

ACM Reference Format:

Denys J.C. Matthies, Ole Sellhorn, Marco Torge Gabrecht, Jörg Schuljak, and Horst Hellbrück. 2023. NOSEwrist: Natural Olfactory Substitution and Extension wrist. In *Mensch und Computer 2023 (MuC '23), September 03–06, 2023, Rapperswil, Switzerland*. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/3603555.3608528>

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MuC '23, September 03–06, 2023, Rapperswil, Switzerland

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ACM ISBN 979-8-4007-0771-1/23/09...\$15.00
<https://doi.org/10.1145/3603555.3608528>

1 INTRODUCTION

Extending the human's capabilities has envisioned by an early HCI pioneer, Douglas Engelbart [8]. Utilizing wearable user interfaces to substitute broken senses and as a natural extensions of our body is meanwhile denoted as Assistive Augmentation [13]. Pattie Maes [15] and other researchers [9] believe that new sensing technology in combination with artificial intelligence will enrich our physical experience in future once technology successfully integrates within our bodies [18]. This seems to be the way to our inevitable future, the Cyber-Human [2].

This paper follows the envisioned trend mentioned while asking: *How can we integrate an artificial olfactory sensor within our body for sensory substitution and body extension?*

In this research, we attached a MEMS gas sensor to the human's wrist, as this body position seems to provide sufficient degrees of freedom and a seamless integration [10, 17].

Our concept can be useful to provide as a substitution for Anosmia (complete loss of smell), hyposmia (smelling disorder), and parosmia (odors are misinterpreted). With the prevalence of COVID-19, the loss of smell and taste seems to be a common side effect [12], demonstrating the usefulness of our augmentation.

In this paper, we contribute:

- a proof-of-concept that enables the discrimination of four typical household liquids found in the kitchen: water, alcohol, fluid accelerant, and vinegar
- a number of ideas for the further development of the system including future application scenarios.

2 RELATED WORK

2.1 Background

Olfactory perception, or the sense of smell, is important for a variety of reasons. It plays a role in the detection and identification of odors, which can be used to locate food, identify potential mates, and detect potential dangers, such as smoke or gas leaks. Additionally, olfaction is closely linked to the limbic system, which is involved in emotional processing, memory, and behavior, so it plays a role in emotional responses, memories and sexual attraction [22]. Olfactory dysfunction can also be an early indicator of neurological disorders such as Alzheimer's disease [3].

The sensitivity of the human olfactory system is incredibly high, allowing us to detect and distinguish between a wide range of odors. Still, it is not as high as the visual or auditory system. Humans can distinguish between a large number of different odors, but not as many as the number of colors or sounds [19].

Sensitivity can vary depending on the individual and the specific odor being detected. Additionally, sensitivity can be affected by factors such as age, disease, and exposure to certain chemicals [11, 23].

Overall, olfactory perception is a complex process that involves both sensitivity and resolution, with these abilities varying depending on the specific odor being detected and the individual perceiving it. Moreover, human shows an "adoption phenomenon", meaning that smells become not perceivable after a certain while of exposure or when introduced slowly over time. This can become a danger and thus gas sensors are developed to support here.

2.2 MEMS Sensors

MEMS (Micro-Electro-Mechanical Systems) sensors are tiny devices that combine mechanical elements, such as levers, beams, and membranes, with electronic components, such as transistors and sensors. These sensors can be used for a wide variety of applications, including accelerometers for measuring motion, gyroscopes for measuring orientation, and pressure sensors for measuring force. They are used in many consumer electronic devices, automobiles, and industrial applications. MEMS gas sensors are the state-of-the-art in gas detection that provide an adaptable solution for various use cases. Their size can also allow for utilizing a combination of them in an assembly without and drastic size increase as seen with other gas sensors [20].

Metal Oxide (MOX) Sensors are use metal oxide semiconductors to detect gases. A MOX sensor can be incorporated into a MEMS device to achieve a tiny form factor. MOX sensors are commonly used for sensing gases such as oxygen, carbon monoxide, and volatile organic compounds. The sensor works by measuring the resistance of the metal oxide material, which changes in the presence of specific gases. They are known for their high sensitivity and low cost, making them suitable for a wide range of applications including air quality monitoring, industrial process control, and safety systems [26].



Figure 1: Left is showing the components, which are a wired gas sensor break-out board, Wio Terminal, 10,000mAh VARTA powerbank, Velcro strips, sock, and a USB cable. The middle photo shows the sensor mounting at the wrist. Right image shows the screen displaying the classified substance.

2.3 Applications

Besides typically known applications, such as sensing smoke and fire [6], other applications have been showcased in research. For instance, recently Zhang et al. [27] demonstrated a whiskey identification with an "electronic noses" that can identify subtle changes in substances. It has an assumable increasing detection sensitivity to an untrained human nose. The authors show how their artifact can identify different types of whiskey [27]. In another project, Benjamin Cabé [5] showcased how an artificial nose can distinguish between the smell from coffee, whiskey, and bread using a gas sensor that can detect CO and NO₂. Cabé 3d-printed a human-looking nose, built-in a microcontroller and trained a neural network on it [5]. A forearm augmentation to enhance environmental awareness of odor signals via a translation into vibrotactile stimuli was proposed by Choi et al. [7]. The authors utilize a MQ-3 gas sensor to detect alcohol. Next to an olfactory augmentation device that complements or replaces human senses, researchers experimented using odors to enrich experiences in HCI [1, 14, 16].

3 NOSEWRIST

3.1 Implementation

3.1.1 Hardware. There are two key components: a gas sensor and Wio Terminal board (see Figure 2). The sensor is a multichannel gas sensor break-out-board¹ that provides stable and reliable gases detecting function with four gas-sensors (GM-102B; GM-302B; GM-502B; GM-702B). It can detect Carbon monoxide (CO), Nitrogen dioxide (NO₂), Ethyl alcohol (C₂H₅CH), Volatile Organic Compounds (VOC) and others.

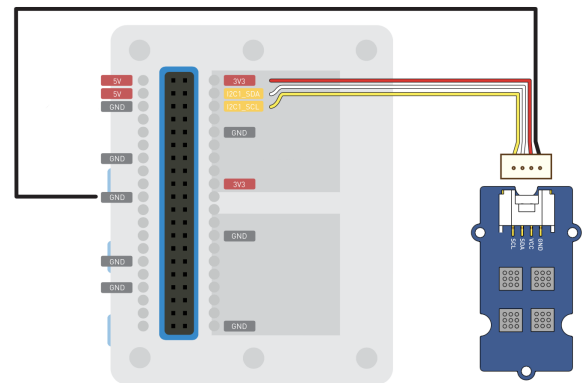


Figure 2: Schematics of wiring of the gas sensor break-out board to the Wio Terminal.

The break-outboard is connected to the Wio Terminal² via the I2C protocol and driven by 3.3V fed from the Wio board. The Wio Terminal is a prototyping platform using an ATSAM51-based microcontroller. It incorporates embedded sensors, such as an Accelerometer, Microphone and a Light & IR Sensor. Also, it uses both Bluetooth and Wi-Fi Wireless connectivity powered by Realtek RTL8720DN and fully compatible with Arduino and MicroPython. The Wio Terminal itself has an integrated 2.4" LCD Screen, which can be used to show information (see Figure 1).

¹<https://www.seeedstudio.com/Grove-Multichannel-Gas-Sensor-v2-p-4569.html>

²<https://www.seeedstudio.com/Wio-Terminal-p-4509.html>

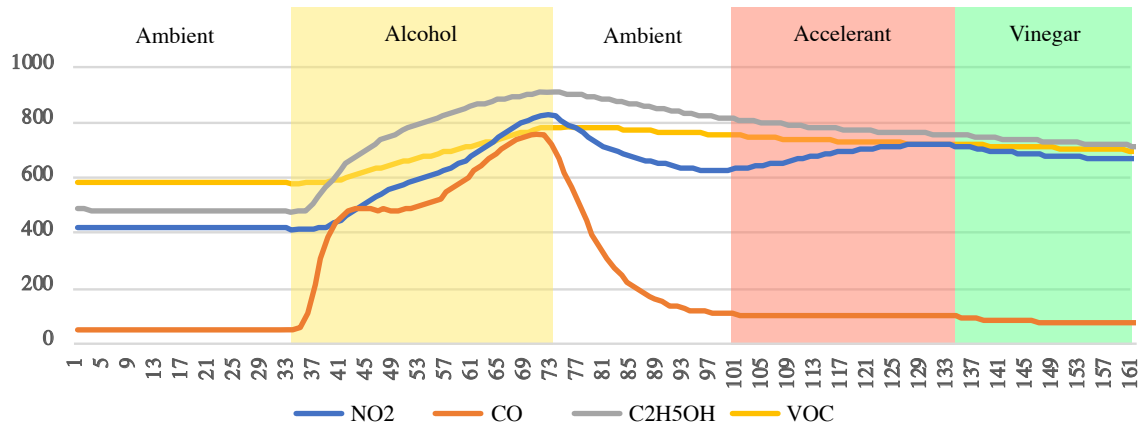


Figure 3: Showing the raw data as collected from the sensor board. The stimulus presented to the sensor is shown on top.

3.1.2 Machine Learning. To accomplish our goal of identifying different substances, we selected a machine learning approach. As a straight-forward solution, we decided to use the tool EdgeImpulse³ for supervised learning. Meaning, we recorded all substances while holding the sensor over them. The training data was rather short and incorporated 30s per substance. On top of that, we recorded a *default*-class, when no substance is present. Our input trajectories are four data streams provided by the sensor board. The data is sampled with 10 Hz. We trained a TinyML neural network offered by EdgeImpulse. The model's layer architecture looks like as follows: Raw Data -> Relu (weights: 20x56, bias: 20) -> Relu (weights: 10x20, bias: 10) -> Dense (weights: 5x10, bias: 5) -> Softmax -> State Output. In total we recorded a total of 5:21 min data and split it into 72% for our training set (3:51 min) and 28% for the test set (1:30 min). We set a sliding window approach with 10% overlap to previous samples, while our window size was 1 second. To ensure convergence of our model, we trained it with 500 epochs and achieved an overall accuracy of 95.65%. We consider this number as rather theoretical as the real-time implementation seemed not to be that robust. To enable a real-time classification without having the device attached to the computer, we uploaded the model to the Wio Terminal.

For the detection, we decided to manually trigger the ML-pipeline by pressing the blue button on the Wio Terminal. We record 1.5s of samples and let the model decide what substance might be present. The result is displayed via a label on the Terminal's display (see Figure 1).

3.2 Demonstrated Application

There are several scenarios where artificial noses, that outperform human olfactory sensation, can support the human. We demonstrate only one useful example application. An artificial nose attached to the wrist can be useful to provide as a substitution for Anosmia (complete loss of smell), hyposmia (smelling disorder), and parosmia (odors are misinterpreted). We selected four typical liquids that can be found in a household and which are only distinguishable via its smell, since their viscosity and appearance are similar to the human eye (see Figure 4). Drinking the "wrong" liquid is dangerous and may result in permanent damage of the human internal tissue.

With our approach, we are able to correctly identify these four liquids when putting the wrist over the glass, such as before drinking. However, as seen in the graph displaying the sensor data, there are certain limitations. Particularly after presenting alcohol to the sensors, we can perceive an enormous peak (see Figure 3). This, on the one hand, makes alcohol easily detectable, however, detecting ambient or water just the moment after alcohol will likely result in a false recognition. This is because the sensor underlie a certain "cool down" as seen in the figure.

In a future these sensors could be implemented as an alternatives or as a substitution in utilizing an artificial nose with MOX sensors. This specialization can be focused on common harmful gases with the '00x' and '30x' series, more chemical-based gasses with the '13x' series, natural gases with the '21x' series, or air quality with the 'AQ' series. Use cases could also implement multiple sensors from each category to provide a wider basis for identification methods such as neural networks. Some gases present here such as carbon monoxide are unscented and could provide an extension of the human nose if utilized in an augmentation feature such as the wrist nose. Besides the 'MQ' series metal oxides sensor variants there its also alternative MEMS sensor types with optical and acoustic detection systems. These sensors could expand the use cases such as medical diagnoses that the MOX sensors would not otherwise identify.

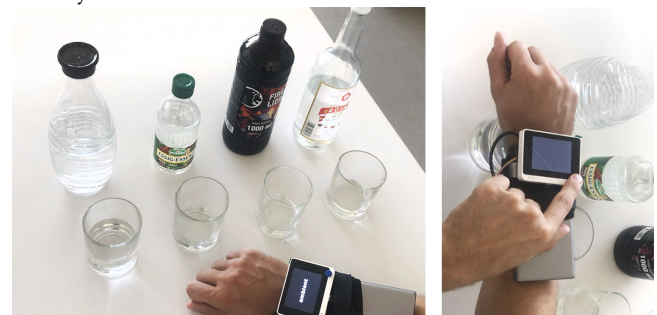


Figure 4: In our demonstration, we classified next to air, our default-class "ambient" and four substances, which are: water, vinegar, accelerant, and alcohol. The wrist is to be held just above the glass that contains the substance of desire. A press on the blue button triggers the detection process.

³<https://www.edgeimpulse.com>

Table 1: Suitable Gas Sensors that are currently available.

Model No.	Detection Capability	Model No.	Detection Capability
MQ-2	Methane, Butane, LPG, smoke	MQ-3	Alcohol, Ethanol, smoke
MQ-4	Methane, CNG Gas	MQ-5	Natural gas, LPG
MQ-6	LPG, butane gas	MQ-7	Carbon Monoxide
MQ-8	Hydrogen Gas	MQ-9	Carbon Monoxide, flammable gasses
MQ-131	Ozone	MQ-135	Benzene, Alcohol, smoke
MQ-136	Hydrogen Sulfide gas	MQ-137	Ammonia
MQ-138	Benzene, Toluene, Alc., Acetone, Propane, Formaldehyde	MQ-214	Methane, Natural gas
MQ-216	Natural gas, Coal gas	MQ-303A	Alcohol, Ethanol, smoke
MQ-306A	LPG, butane gas	MQ-307A	Carbon Monoxide
MQ-309A	Carbon Monoxide, flammable gasses	MG811	Carbon Dioxide (CO ₂)
AQ-104	Air quality	AQ-2	Flammable gasses, smoke
AQ-3	Alcohol, Benzene	AQ-7	Carbon Monoxide

4 POSSIBLE ADVANCEMENTS

Sensors: In this paper we describe the use of MEMS gas sensors mounted on the wrist as the primary means of detecting and distinguishing different liquids. An advancement would include exploring different types of sensors, such as electronic nose sensors or other chemical sensors, and determining their effectiveness for this and other applications.

Machine learning model: Also, we utilize a machine learning model to discriminate between different liquids as this can be considered the state-of-the-art. An advancement would include exploring different types of models, conventional and different neural networks architectures, with the ultimate goal of determining the effectiveness for such applications.

Detection delay: To overcome the detection delay, we envision to use redundant sensors which could shutter every few seconds. As our sensor board is particularly designed to detect alcohol, we suggest to add a number of different sensors (see Table 1), so other substances are also easier detectable.

Wearable design: Augmenting the human body is described by a wrist-mounting as the primary means of delivering the olfactory augmentation. However, a potential further development includes exploring different forms of wearable devices, such as a ring or a pendant, and determining which provide the most seamless integration with the body. Another option is going beyond wearables and tapping into implant-like devices.

User interface: The current implementation of the user interface is a button that needs to be pressed. In future one would explore different ways for the user to interact with the device and with the environments, such as through an implicit way of interaction and by a feedback loop through the smartphone and other devices.

Use cases: We see the technology to have potential to be utilized in a variety of other ways, beyond just substituting a broken sense. An advancement would include exploring different use cases, such as in the culinary industry, or for people with certain medical conditions, and determining which are most practical and beneficial.

Safety and security: Although often neglected in this type of research, one should also explore the consideration of safety and security aspects, as well as how to ensure the privacy of the user and data.

Human factors: Finally, one needs to consider how to make the device comfortable to wear and use, how to ensure it doesn't cause any discomfort, and how to make it accessible to people with different abilities.

5 APPLICATION SCENARIOS

Scenario 1 - Warning of Hazardous Substances: A wearable gas sensor mounted to the wrist could warn of hazardous substances by detecting and identifying specific chemicals present in the air. The sensor would be connected to a device that would analyze the data similarly to the Wio Terminal and trigger an alarm or warning to the user once a hazardous chemical is identified. The warning could be a visual, auditory or haptic, for example, a vibration or a sound. A cloud-based machine learning could allow for up-to-date classifications and be calibrated to detect a specific range of chemicals that are known in the database of known hazardous substances. A real-time monitoring of the concentration level could provide a recommended course of action, such as evacuating the area or seek medical attention.

Scenario 2 Identify Individuals: There are conditions at which humans are unable to recognize familiar faces, such as Alzheimer. In bad light conditions, camera sensing is compromised. Analyzing specific chemicals present in the air, such as a person's breath or sweat is another opportunity to help here. This would require a sophisticated machine learning model and sensor calibration to detect and distinguish the unique chemical signature of an individual. One way to achieve this would be to train the machine learning model on a large dataset of chemical signatures from different individuals, and then use this trained model to identify individuals based on new sensor readings. It's worth noting that there are several limitations to consider. For example, factors such as changes in diet, medication, and medical conditions could affect the chemical signature of an individual, and make identification less reliable. Also important to consider are ethical and legal implications when identifying individuals, as it raises privacy and security concerns.

Scenario 3 - Tracking Hormone Balance: A wearable gas sensor could be used to track hormone balance and identify ovulation by detecting and analyzing specific chemicals present in the air, such as hormones present in a person's breath or sweat. A sophisticated

machine learning model may be trained on a large dataset of chemical signatures, which might be also user-dependent. From female individuals, identifying different stages of their menstrual cycle, and ultimately identifying ovulation might be feasible. The sensor might be calibrated to detect a specific range of chemicals, such as estrogen, progesterone, and luteinizing hormone (LH), which are related to ovulation. This kind of technology might not replace a medical diagnostic or advice, instead it could be used in conjunction with other medical methods.

Scenario 4 - Blood Glucose Measurement: A sophisticated machine learning model with gas sensor may enable the detection of unique chemical signatures of glucose. Meanwhile, literature has proven to measure the blood sugar value (β -hydroxybutyrate) with concentration of breath acetone [25]. With an electronic nose it is possible to detect a change in blood sugar [21, 24]. This method is non-invasive and painless. However, it requires exploration, because of the incremental changes happening over time. Previous laboratory studies show promising results. However, in real-world the error-rate of an neural network was 23,76% [24]. With more sophisticated sensors, and different sensor positions, such as integrating these into panties, results will improve, since glycemia is also present in urine.

Scenario 5 - Odem Classification: One way to achieve the identification of odem (breath) would be to train the machine learning model on a large dataset of chemical signatures from individuals with different breath qualities, such as healthy individuals and individuals with respiratory conditions, and then use this trained model to classify breath quality based on new sensor readings. The sensor would have to be calibrated to detect a specific range of chemicals that are found in breath such as carbon dioxide, oxygen, and volatile organic compounds (VOCs). The device could then notify the user of their breath quality and provide feedback or recommendations, such as seek medical attention or try to improve breathing techniques. Also, unpleasant odor could be detected and suggestions could be made by the system.

Scenario 6 - Pollen Measurement: Allergy sufferers could benefit from the detection of specific pollen by chemicals present in the air. As previously envisioned, we suggest to train a machine learning model on a large dataset of chemical signatures from different types of pollen. The system would have to be calibrated to detect a specific range of chemicals that are found in pollen such as proteins, enzymes, and lipids. The device could then notify the user of the presence of a specific type of pollen and its concentration level, which could help allergy sufferers to take preventative measures such as taking medication or avoiding certain areas.

6 CONCLUSION & FUTURE WORK

In this paper, we demonstrated a proof-of-concept body augmentation - a wrist-mounted olfactory system. We showed the discrimination of four typical household liquids such as water, alcohol, fluid accelerant, and vinegar. Furthermore, we explored and discussed the further developments for olfactory sensation augmentation.

In future, we envision to improve sensitivity by advancing the prototype, such as incorporating a heated air chamber. To improve response time, one can use redundant sensors and shutter between them. Moreover, alternative feedback beyond a display is to be explored. Related work has shown audio feedback via bone-conduction to be an alternative [4].

ACKNOWLEDGMENTS

This publication results from research of project PASBADIA funded by the Joachim Herz Stiftung, Germany (Id 120002).

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