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DESIGN OF ELECTRONIC NOSE BY USING MOS SENSORS

The Mini Project report submitted in partial fulfilment of requirements for the award of degree of

Bachelor of Technology in Electronics and Communication Engineering

Submitted By

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<u>CERTIFICATE</u>

This is to certify that the mini project work titled **DESIGN OF ELECTRONIC NOSE USING MOS SENSORS** a bona fide record of the work done by **Singuru Sai Shankar (19131A04M5)** to the Department of Electronics and Communication Engineering, **Gayatri Vidya Parishad College of Engineering (Autonomous)**, **Visakhapatnam**, affiliated to **Jawaharlal Nehru Technological University**, **Kakinada** in partial fulfilment of the requirement the award of the degree of **Bachelor of Technology** in **Electronics And Communication Engineering** during the academic year 2019-23.

Signature of the Guide	Signature of the HoD
Dr. D.B.V. JAGANNADHAM	Dr . N Deepika Rani
Professor	Professor and HoD
Dept. of ECE	Dept. of ECE
GVP College of Engineering	GVP College of Engineering

DECLARATION

I hereby declare that this project entitled ***"DESIGN OF ELECTRONIC NOSE USING MOS SENSORS"*** **is** a bona fide work done by me and submitted to **the Department of Electronics and Communication Engineering, Gayatri Vidya Parishad College of Engineering (Autonomous), Visakhapatnam**, in partial fulfilment for the award of the degree of B.Tech is of own and it is not submitted to any other university or has been published any time before.

Place: Visakhapatnam

Date:

By

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By,

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ABSTRACT

From the initial attempts to mimic the human nose with artificial devices, a variety of sensors have been developed, from biological and light gas detectors to bio-sensing materials comprising proteins of the biological olfactory system. To design a device that can emulate the human nose, two major issues that still need to be addressed are the complexity of the aroma coding and the extreme sensitivity of the biological system.

So far, 300-400 inactive olfactory receptors, still orphaned, are far from broken human sense code. The abnormal sensitivity of the human nose based on growth techniques that are difficult to reproduce through electrical circuits Ways are needed to address this issue by reviewing the publications on chemical and biological systems and tools being developed, and then try to establish a modern state in the design of the electronic nose.

The aim of this project is to design an electronic nose which can detect various odours with the use of metal oxide sensors and machine learning algorithms. To achieve this goal an extensive review of various publications of human nose and metal oxide sensors is performed to propose an efficient design in odour prediction.

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CHAPTER 1

INTRODUCTION

Over the last decade e-sensing technologies have experienced important developments from a specialized and marketable point of view. The electronic nose is a fairly new tool that may be used for safety, quality, or process monitoring, negotiating in procedures that may presently bear days to complete. Electronic Nose is a smart instrument that's designed to descry and distinguish among complex odours using an array of detectors developed.

1.1 OBJECTIVE:

- The objective of the study is to design an electronic nose.
- To differentiate various odours based on their chemical properties – obtaining the ‘odourprint’.
- To increase the efficiency of the odour prediction by the use of sensor array.

1.2 ABOUT THE PROJECT:

An electronic nose is designed to be capable of identifying chemical compounds through sensing and analysing odour molecules. As a kind of machine olfaction, e-nose technology has the great potential to be applied in different fields. Based on the human olfactory system, and the similarities between human olfactory system and e-nose system.

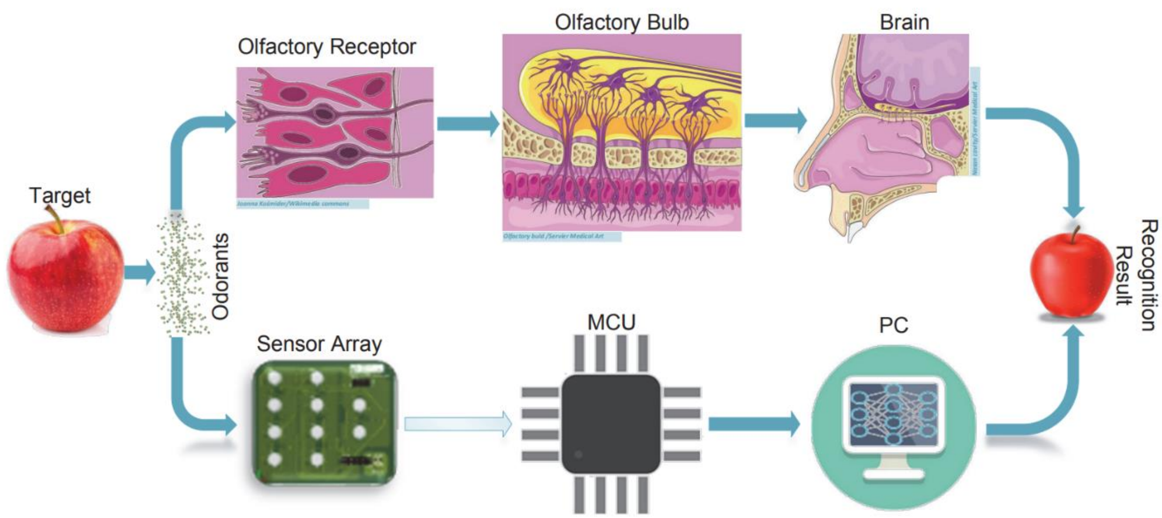

Fig.1.1 Workflow of the proposed system

A sensor array is used to mimic the olfactory receptor (OR) to transform the odorants information to the electrical signals. These signals can be processed by the "olfactory bulb" of the e-nose which is a micro-controller. To recognise the odorants information, a computer is used to represent the brain, and the pattern recognition algorithms are the "content of the brain" in this computer.

Metal oxide gas sensors are chosen as the primary sensor array solution considering their high efficacy and popularity in the global market. Signal Conditioning circuits are designed to remove noise from the outputs of these gas sensors. A reliable power system will also improve the signal quality by providing the stable and clean power rails for the whole system. Moreover, an external performance analogue to the digital (A/D) unit will help to improve the accuracy of A/D conversion tasks, and transmit the signals rapidly to the reliable digital signal processor (DSP) for further processing. In addition, some electrical/signal isolation design will also help to improve the reliability of the e-nose system

Data analysis methods (e.g feature extraction, pattern analysis, etc.) are used to detect different items by recognising the "odour-prints" which is the unique signal matrix generated by gas sensor arrays according to different odour sources. The conventional electronic amplifiers can improve the signals, but they provide a constant gain so it is replaced by a programmable amplifier provides a relative gain to produce a same output level.

Feature	Biological Noses	Artificial Noses
Type of sensing elements	Membrane receptors of broad overlapping specificity	Macromolecules with a moderate degree of specificity (OBPs, other binding proteins, DNA)
Number of sensing elements	About 300 in humans, up to 1000 in other mammals, around 100 in insects	At least 100 types to mimic the discrimination and the wide range of odours detected by the human nose
Coding strategy	Discrimination mainly on the basis of stereochemical parameters, but in some cases also of functional groups	Stereochemical parameters and functional groups

Table 1.1 Biological Noses v/s Artificial Noses

CHAPTER 2

MOS-SENSORS FOR ARTIFICIAL OLFACTION

2.1. INTRODUCTION:

The MOS SENSORS generally comprises a ceramic support tube containing a platinum heater coil onto which sintered $SnO2$ is carpeted onto the outside of the tube with any catalytic complements. Gas samples are detected by the change in the electrical resistance of the essence oxide semi-conductor. Resistance changes due to combustion reactions occurring within the lattice oxygen species on the surface of metal oxide particles

This kind of transistors operates by means of three contacts, two allow the current in (source) and out (drain), and third acts as the gate and regulates the current through the transistor. When a voltage is applied on the gate, an electric field is generated which affects the transistor conductivity. If vapour (polar compounds) interacts with the gate, then the current flowing through the transistor sensor) changes and a shift of the conductance is produced. The interaction between the vapour and the gate depends on the gate structure; it can be thin, made of a porous metal film (6-20 nm), or thick, built with a dense metal film (100-200 nm). The latter kind of gate (transistor) works well with vapours containing molecules that can dissociate hydrogen, because these atoms lead to a potential change in this kind of transistor. Almost all kind of compounds, however, respond well when the gate is thin, due to the probable mechanisms of voltage shifts.

2.1 LIST OF SENSORS:

TGS2602:

The TGS 2602 has high sensitivity to low concentrations of odorous gases such as ammonia and H2S generated from waste materials in office and home environments. The sensor also has high sensitivity to low concentrations of VOCs such as toluene emitted from wood finishing and construction products

TGS2603:

The TGS 2603 has high sensitivity to low concentrations of odorous gases such as amine-series and sulphurous odours generated from waste materials or spoiled foods such as fish. By utilizing the change ratio of sensor resistance from the resistance in clean air as the relative response, human perception of air contaminants can be simulated and practical air quality control can be achieved.

TGS2600:

TGS 2610is a semiconductor type gas sensor which combines very high sensitivity to LP gas with low power consumption and long life. Due to miniaturization of its sensing chip, TGS2610 requires a heater current of only 56mA and the device is housed in a standard TO-5 package.

TGS2620:

The TGS 2620 has high sensitivity to the vapours of organic solvents as well as other volatile vapours, making it suitable for organic vapor detectors/alarms. Due to miniaturization of the sensing chip, TGS 2620 requires a heater current of only 42mA and the device is housed in a standard TO-5 package.

2.2 PROPOSED SYSTEM:

Generally, odour sensors are designed to detect some specific odour. Each of the odour sensors has characteristics that respond to different odours. When many odour sensors are combined in one system, their ability to detect an odour is increased.

Selectivity is an important property of gas sensors and is the ability of a sensor to respond to a particular gas in the presence of other gases. The selectivity in detecting the gases is increased by implementing an array of sensors which in turn ensures high sensitivity.

The sensitivity of different sensors to the gases is provided in the table below:

Sensor Name	Target Gases
Sensor 1: TGS 2620	Ethanol, Hydrogen, Iso-butane, CO, Methane, etc.
Sensor 2: TGS 2602	VOCs, Ammonia, H_2S, etc.
Sensor 3: TGS 2600	Hydrogen, Ethanol, Iso-butane, etc.
Sensor 4: TGS 2603	Trimethylamine, Methyl mercaptan, etc.

Table 2.1 Sensitivity of different sensors

CHAPTER 3

SIGNAL CONDITIONING

The raw response obtained directly from the chemical sensor array cannot be used in the e-nose system due to its low signal-to-noise ratio (SNR) and the sensor drift. A pre-processing step is therefore needed. Pre-processing is a technique in which transform the raw data into a meaningful and understandable format. Real-world data is commonly incomplete and inconsistent because it contains lots of errors and null values. A good, pre-processed data always yields to a good result. Various Data pre-processing methods are used to handle incomplete and inconsistent data like as handling missing values, outlier detection, data discretization, data reduction (dimension and numerosity reduction), etc.

3.1 SYSTEM ARCHITECTURE:

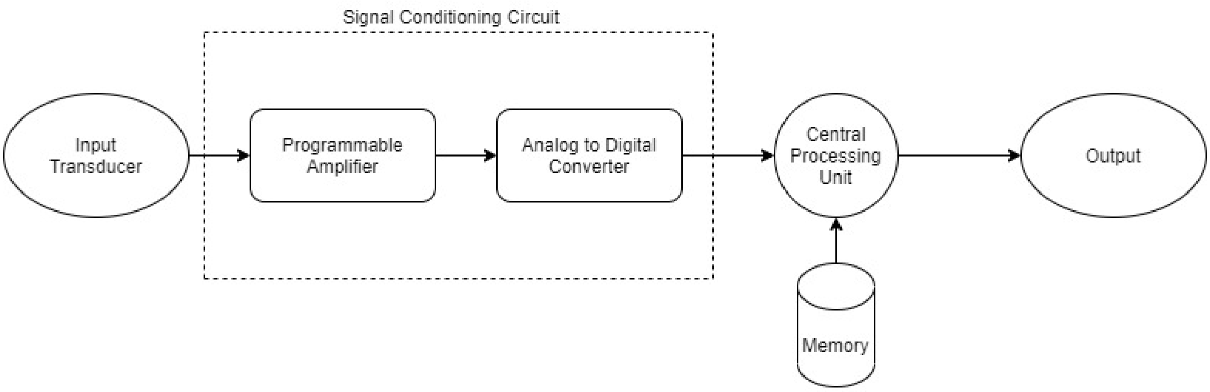

Fig 3.1 Architecture of the proposed system

3.2 DATA COLLECTION:

The quantity & quality of your data dictate how accurate our model is. The outcome of this step is generally a representation of data which will be used for training. Data used is pre-collected data. It’s the most crucial aspect that makes algorithm training possible and explains the popularity of machine learning in present days.

3.3 FEATURE EXTRACTION:

Feature extraction of gas sensor steady-state responses are widely used in odour classification. Applications of feature extraction methods generally fall into two categories: manual extraction using expert knowledge and automatic methods that are data focused. To extract four features are chosen, maximum response value , time interval between gas-in and maximum 1st derivative of response , time interval between gas-in and maximum 2nd derivative of response, and integral between time of gas-in and time of peak.

3.4 CLASSIFICATION ALGORITHM:

To verify the performance of the system, one of the most popular classification algorithms. Support Vector Machine (SVM) is an effective algorithm in dealing with classification problems. An SVM learns a discriminant function that separates positive and negative examples with the maximum margin. The objective of SVM is to find an optimal hyperplane to separate two different classes of samples.

CHAPTER 4

BREATH CLASSIFICATION

4.1 INTRODUCTION:

The study of exhaled breath for health diagnosis and monitoring is becoming an increasingly popular area of research. Unlike most traditional health monitoring and diagnosis through the use of bodily fluids, breath collection is non-invasive and convenient. Furthermore, studies have shown there are many metabolomic compounds in human breath that could be used for health monitoring and disease diagnosis.

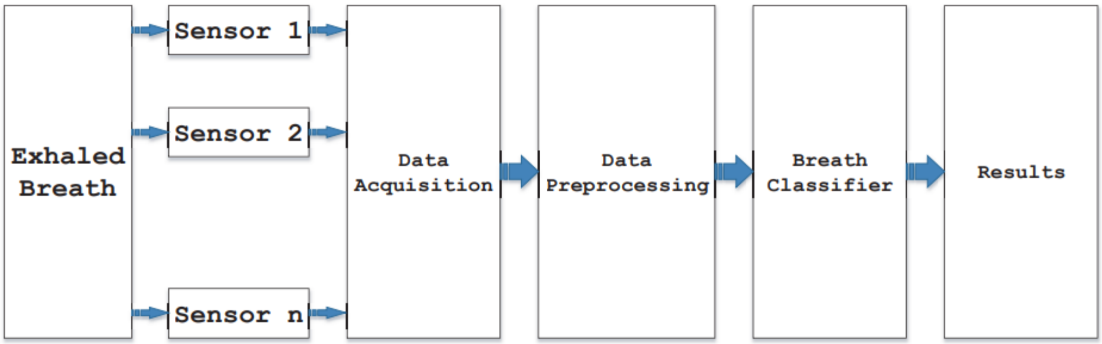

Fig 4.1 Block diagram for breath classification

4.2 EXPERIMENTAL SETUP:

Pre-collected data set of breaths is used in the experiment Normal breath samples were collected first, followed by smoking, and then alcohol consumption. Between normal and smoking samples, the equipment was allowed to run a blank for 115 minutes in order to ensure no sample was left in the air system. The volunteer spent 5 minutes smoking one cigarette just before smoking samples were taken. Between the smoking and alcohol consumption samples, the equipment was cleaned for 110 min by allowing room air to flow through the system.

The odour datasets used in this chapter were collected under 25 °C to 27 °C ambient temperature and 60% RH ambient humidity.

4.3 CLASSIFICATION:

The full dataset is partitioned into training and test sets by randomly selecting 20% of the data from each scenario to form the test set and the remaining for the training set. This process was performed five times: where each data sample appears exactly once in a test set.

SVM was run as a binary classifier as well as a multi-class classifier. In the former case, two scenarios were tested against each other, thus yielding three classification problems: normal vs. smoking, normal vs. alcohol, and smoking vs. alcohol. The RBF kernel ($C = 901$, $\sigma = 6.01$) is implemented in the binary SVM classifier. In the multi-class classification, one-versus-one strategy is applied. It evaluates all possible pairwise classifiers and thus induces $k(k - 1)/2$ (where k is the number of classes) individual binary classifiers.

4.4 VALIDATION:

The validation of the different odours is very essential in determining the accuracy of the system.

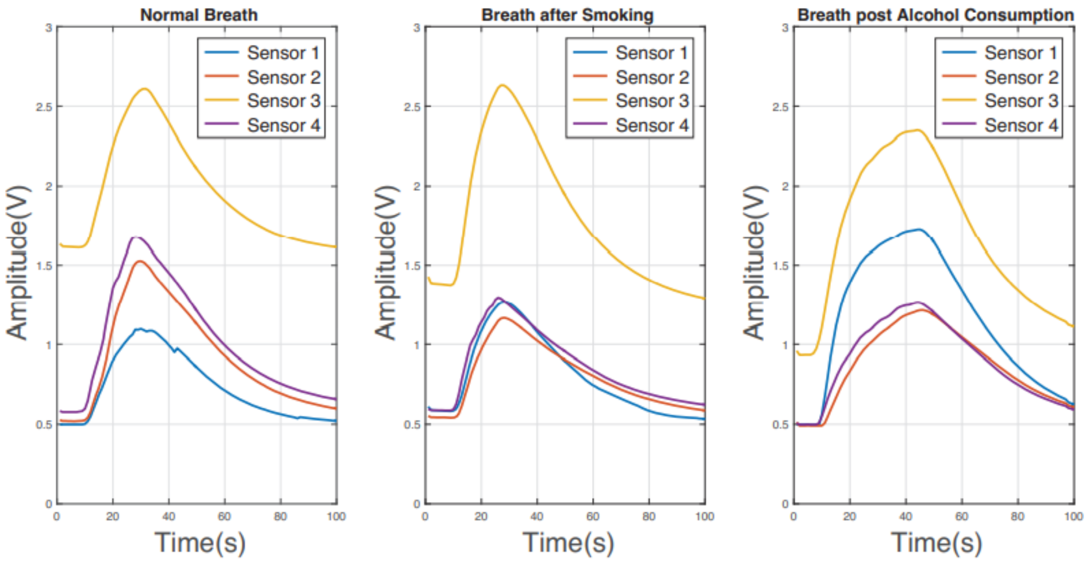

Fig 4.2 Response of different sensors

The simulated responses of the gas sensor array under the three proposed scenarios are plotted in the above graphs. The odours are differentiated based on their difference in response to the sensors. The sensor array gives different response for the different odours due to the different chemical properties due to which there is a variation in conduction of MOS sensors which is characterized as the odourprint for each classification.

4.5 RESULTS:

The accuracy of identification for the normal breath and smoking breath samples lies on 97.5%. Moreover, for the multi-classification task, we can identify these three breath types with 98.334% classification accuracy.

Breath Scenarios	SVM Classification Accuracy
Normal *VS* Cigarette	97.5%
Normal *VS* Wine	100%
Wine *VS* Cigarette	95%
Normal *VS* Cigarette *VS* Wine	98.334%

Table 4.1 SVM Accuracy for different scenarios

From the table, it was evident that when separating breath samples post alcohol consumption with normal and smoking breath samples, 100% and 95% classification accuracy were achieved, respectively.

According to these preliminary test results, the above system can identify different human breath under three different common conditions, which means the proposed solution has certain possibilities to implement to monitor the human health conditions with well-trained data processing algorithms

CHAPTER 5

5.1 CONCLUSION AND FUTURE SCOPE:

Odour classification is a challenging machine learning problem with a high dimensional singularity in the feature set and imbalance of datasets in the present outliers and noise problem. Higher efficiency is observed in the results with the use of sensor array. Using simple features from the responses and support vector machine classifier, it is easy to distinguish the breaths from each scenario. High classification accuracy of over 95% is achieved in all comparisons.

The study of exhaled breath for health diagnosis and monitoring is becoming an increasingly popular area of research. Unlike most traditional health monitoring and diagnosis through the use of bodily fluids, breath collection is non-invasive and convenient. Metabolomics are influenced by an individual's lifestyle, diet, and the environment. These factors make breath analysis an attractive option for personalised health care.

Future works will continue to develop the platform and improve the performance of the airflow control in the system. The intent is to build more prototypes to validate its repeatability before implementing in different applications like food quality assessment, illicit drug detection, wildlife products identification, etc. Finally, a remote e-nose system based on the cloud and Narrow band Internet of Things (NB-IoT) technologies can be built.

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