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Design and Implementation of Oral Odor Detection System for Diabetic Patients

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The oral odor of human beings is directly related to the disease of the human body. The content of acetone in the exhaled gas can be used as an important basis for judging diabetes. Based on the electronic nose (e-nose) technology, this paper optimizes the metal oxide semiconductor gas sensor array in the gas collection system to design a non-invasive early oral odor detection system for diabetes. The original data is reduced in dimension by principal component analysis algorithm and artificial neural network algorithm. The experimental results show that the oral odor detection system has high identification and accuracy for the content of acetone in the exhaled gas. The accuracy of sample identification on fasting is 85%, and the accuracy rate is up to 98% one hour after meal, and it is 92% two hours after meal. This study provides theoretical guidance for early non-invasive diagnosis of diabetes.

1. Introduction

In recent years, with the development of biochips and biotechnology, the research of e-nose technology (Arshak, 2013) has been deepened. This electronic system that imitates human sense of smell is widely used (Wilson, 2009) for ambient air quality monitoring, food and beverage (Ampuero, 2003 & Dutta, 2003) and other volatile odor identification and classification, water quality monitoring and clinical medicine (Dragonieri, 2007) and many other fields. The research of e-nose technology involves sensors, biomimetic materials, computers, signal processing and pattern recognition, and is one of the hottest research directions in the world.
The oral odor of human beings is directly related to the diseases of the human body. This is an important theoretical basis for the four diagnostic methods of traditional Chinese medicine (TCM), that is to look, listen, question and feel the pulse (Manolis, 1983). The application of e-nose technology has replaced the uncertainty of TCM which relies on subjective experiences to diagnose diseases, making the diagnosis of TCM more standardized and objective, which helps to improve the clinical diagnosis of TCM (Risby, 2006). Diagnosing disease by detecting oral odor (Tonzetich, 1991) is safe, rapid, and harmless, and is important for early detection of certain diseases (Mazzatenta, 2013 & Zhi, 2003). So how to find a sensor with sufficient sensitivity is especially important. The existing e-nose system is not targeted for the detection of diseases, and the accuracy needs to be improved. Based on the existing e-nose systems, this paper optimizes the sensor in the gas collection system and designs a detection system suitable for detecting diabetes quickly and accurately.

2. Theoretical basis

2.1 Respiratory diagnosis

Human exhaled gases contain more than 200 volatile organic compounds (VOCs) (Berkel, 2008). The content of these chemical molecules varies widely between patients with different diseases and healthy people. Respiratory diagnosis (Mutlu, 2001) is to determine the disease by detecting the amount of certain gases in the exhaled gas. Table (1) below lists the relationship between exhaled gases and underlying diseases. For example, patients with kidney disease have higher levels of ammonia exhaled (Chan, 2009). The amount of

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acetone in exhaled gases from diabetic patients is higher. These gases have odors that not only reflect the health of the body, but also seriously affect people's mental health and their social contact.

Table 1: Relationship between gas composition in respiratory gases and diseases

Respiratory Gas Maker	Possible Indication of Disease
Nitric Oxide	Asthma and Airway Inflammation
Pentane and Carbon Disulfide	Schizophrenia
Acetone	Diabetes
Ammonia	Kidney disease and uremia
Dimethyl Sulfide	Liver Disease
Benzene, Hepone and Cyclohexane	Tuberculosis

2.2 Detection of diabetes

Diabetes is a chronic disease that endangers human health. It is characterized by elevated blood sugar, disordered body metabolism, and it may cause serious complications. In recent years, the incidence of the disease has shown a trend of younger age. Diabetes is directly related to the ketoacid content in the blood. The amount of acetone exhaled by diabetic patients is about twice that of normal people (Yu, 2005), and for some patients, it's even up to $12\text{x}10^{-6}$. Detection of the conditions of diabetic patients by detecting ketoacid content in blood or urine is costly and long-lasting (Mueller, 2010); early detection of diabetes can be achieved using e-nose technology, which is conducive to timely treatment of diabetes, meanwhile it's also helpful for the monitoring of the condition of patients already with diabetes.

3. E-nose system

3.1 Basic structure and working principle of e-nose

The e-nose system is a device that combines multiple gas sensors with appropriate pattern classification methods to analyze, identify and detect complex odors. It is a human-like olfactory system, which is mainly composed of a sample processor, a gas sensor array, and a signal processing system. The following figure (1) is the basic principle diagram of the operation of the e-nose oral odor detection system.

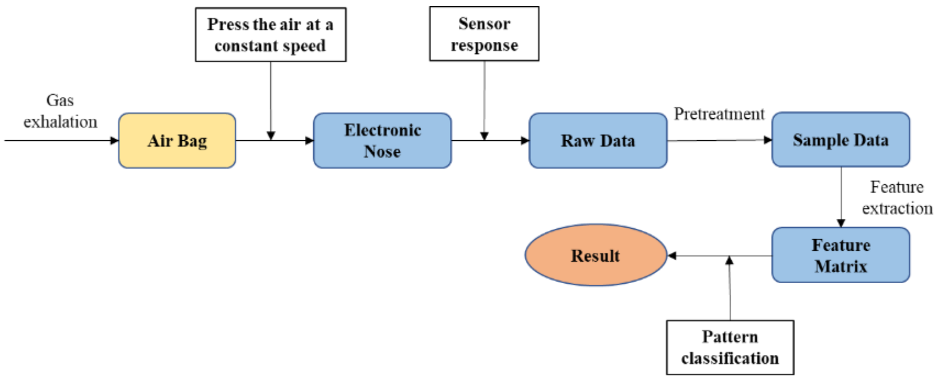

Figure 1: System working principle block diagram

First, the gas exhaled by the patient is pressed into the gas sensor array at a certain speed through the air bag, the resistance changes after it reacts with the gas sensor, the gas signal is converted into an analog signal output, and these signals contain data of the gas composition of the sample, and then the data is pre-processed and passed through the pattern recognition unit to output the results.

3.2 Gas sensor

In the oral odor detection system, the sensor is a component that directly contacts the gas to be tested, and the gas data collected by the gas sensor has an important effect on subsequent data processing. Therefore, selecting a suitable sensor is the key of the entire detection system. When selecting a gas sensor, it is mainly necessary to meet the following technical indicators, as shown in Figure (2). At present, gas sensors that are commonly used in e-nose systems include metal (Li, 2018) oxide sensors, electrochemical sensors, and conductive polymer semiconductor (Wu et al., 2018) sensors.

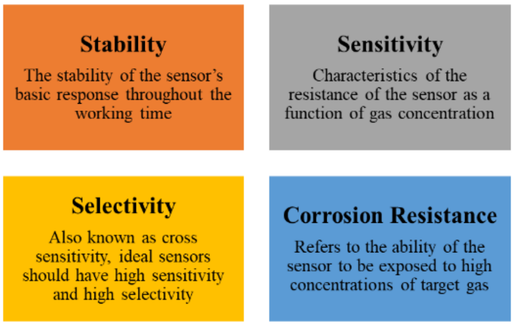

Figure 2: Gas sensor specifications

The structural composition of the gas sensor is shown in Figure (3). It mainly consists of sensors, processors and related circuits. It can use the internal micro-processor's storage and computing power to adjust the internal behavior of the sensor, so that high-quality and effective data can be collected to prepare for the next data processing.

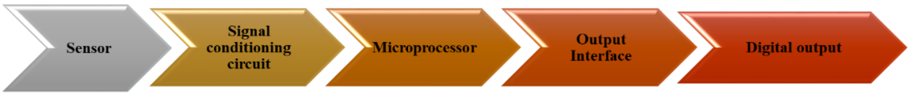

Figure 3: Smart sensor structure frame

3.3 Pattern recognition algorithm

In the oral odor detection system, besides the performance of the sensor, the pattern recognition algorithm of the signal is also a focus of the research. In the recognition of signal patterns, the reduction of high-dimensional gas signals into low-dimensional signals that can be processed by computers is the key to signal recognition. Principal Component Analysis is a method of reducing the dimension by removing high-order components and retaining low-order principal components, it has good effects on the aggregation of similar samples, however, the classification effect obtained according to the difference of sample characteristics is also different, and it cannot be directly used for the identification of odor results, it needs to combine with artificial neural networks and other methods to achieve the purpose of identifying gases.
After Principal Component Analysis, the components have the following main properties:
(1) $E(y_i) = E\left(u_j^T x\right) = 0$, that is, the mean value of each principal component is zero;
(2) $\mathrm{Var}\left(y_j\right) = \varphi_j$, that is, the variance of each principal component is equal to each eigenvalue of the correlation matrix;
(3) Cov $(y_j, y_j) = 0$, that is, the covariance between any two principal components is zero.

4. Construction of oral odor detection system

The oral odor detection system is mainly composed of two parts: hardware system and software system, as shown in Figure (4).

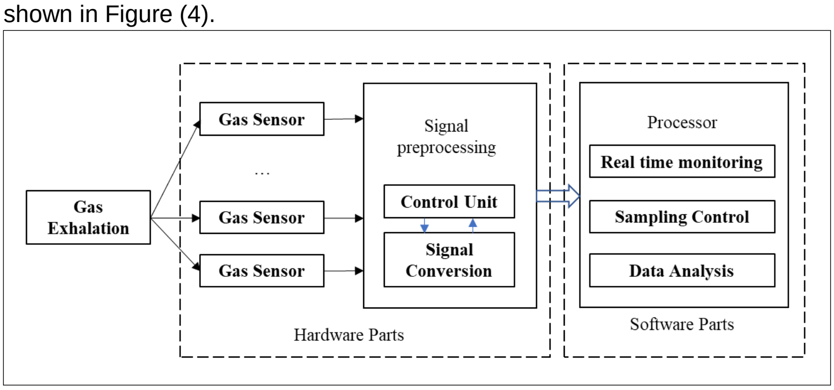

Figure 4: Human oral odor detection system

4.1 Hardware design

4.1.1 Data collection system

The oral odor detection system collects gas exhaled by healthy people and diabetic patients through a sensor array, the array is mainly composed of sensors for detecting different gas components, the following figure (5) is a structural diagram of the collection system. In the process of gas collection, in order to avoid the differences in vital capacities or personal factors, we store the samples into sample bags with a certain capacity as buffer containers for the detection.
The main gas measured by this system is acetone, and a metal oxide semiconductor gas sensor with high sensitivity to acetone is selected to form the sensor array. The gas collection system consists of eight sensors with high sensitivity, as shown in Figure (6), each sensor is for a specific component.

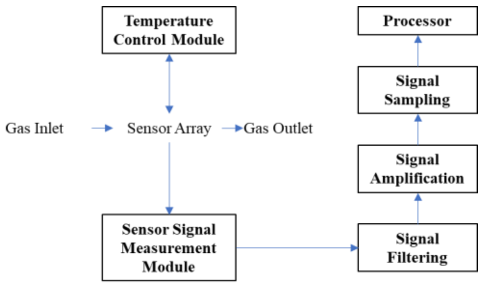

Figure 5: Gas collection system structure

Figure 6: Human oral odor detection system

4.1.2 Data preprocessing

In the process of data collection, it will be interfered by external factors such as the experimental environment. Therefore, in order to obtain accurate experimental results for subsequent data processing, the data collected by the sensor should be pre-processed to amplify the data signals and eliminate errors caused by human and environmental conditions. At the same time, the data is standardized to conveniently and intuitively distinguish the response curves of healthy people and patients. Several commonly used standardization methods for data processing are shown in Table (2) below.

Table 2: Standardized method

Standardized Method	Expression Form
Range Scale	$A_{ij} = \dfrac{A_{ij} - \min(A_j)}{\max(A_j) - \min(A_j)}$
Auto Scaling	$A_{ij} = \dfrac{A_{ij} - \text{mean}(A)}{\text{std}(A)}$
Local Method	$A_{ij} = A_{ij} / \sqrt{\sum_{j=1}^{n} A_{ij}^2}$
Relative Scale	$A_{ij} = \dfrac{A_{ij}}{\max(A)}$

4.1.3 Extraction of feature quantities

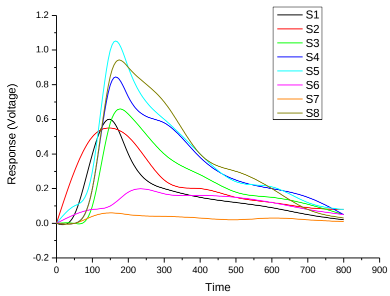

Figure 7: Characteristic curve of healthy people

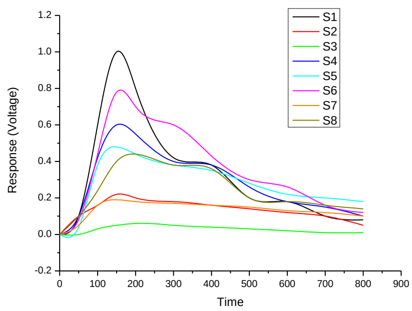

Figure 8: Characteristic curve of diabetic patients

The oral odor detection system contains 8 gas sensors, and the whole process adopts dynamic feature extraction. The characteristic curve includes the rate of change of peaks and troughs. The characteristic curves of healthy people and diabetic patients are shown in the following figures (7) and (8), respectively.

4.2 Software design

The software design of the system is realized by Visual C++. Through programming, it realizes a series of processes such as data collection, sensor signal transformation and feature extraction, and finally realizes the analysis and identification of oral gases, so as to achieve the purpose of detecting diabetes patients. The flow chart of the software design is shown in Figure (9).

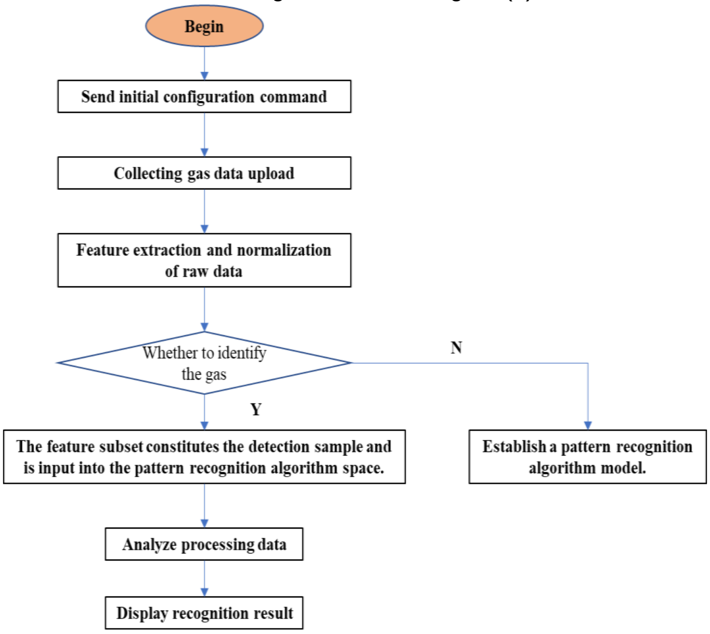

Figure 9: Software Design Flow Chart

4.3 Experimental results and discussion

Classification experiments were conducted on diabetic patients and healthy people using the oral odor detection system. The study subjects were 100 people, 50 males and 50 females, aged between 25 and 55 years old. Among them, there were 40 patients with diabetes, 20 males and 20 females. The diagnostic criteria for diabetes are based on venous blood glucose >11.1mmol/L or fasting blood glucose >7.0mmol/L, and there are other symptoms of diabetes such as polyphagia, polyuria, weight loss, etc.

The oral odor detection system distinguishes healthy people from diabetic patients by measuring the acetone content of the breath exhaled by the test subjects, and the test is required to be tested on an empty stomach, one hour after meal, and two hours after meal. When the acetone content is greater than 100 ppm, the test subject may be a diabetic patient. The experimental results are shown in Figure (10) below.

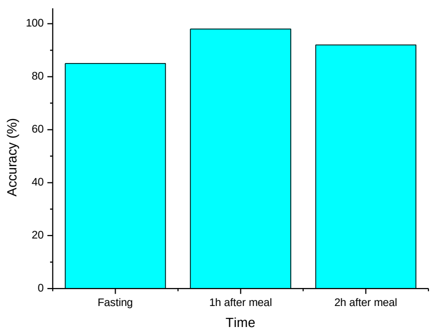

Figure 10: The Accuracy of the system

The accuracy rate on an empty stomach was 84%, the accuracy rate was 98% for one hour after meal, and the accuracy rate was 92% for two hours after meal. The reason for the results of the experiment is that the patients with diabetes have different conditions, and there are three categories of slight, medium and heavy. The patients with slight conditions have an acetone content just below the standard on an empty stomach, thus causing errors. Therefore, the test results of one hour after meal are more accurate.

5. Conclusion

Based on the existing e-nose system, this paper optimizes the sensor in the gas collection system to design a detection system suitable for rapid and accurate detection of diabetes. The specific research results are as follows:

(1) This paper introduced the basic structure and basic principle of the e-nose system, designed the hardware and software of the oral odor detection system for diabetic patients, and used the artificial neural network and principal component analysis method to reduce the dimension of the collected data to improve the identification accuracy of subsequent gas detection.

(2) The oral odor detection system has high identification and accuracy for the content of acetone in the exhaled gases, the accuracy of the sample identification on the fasting was 85%, the accuracy rate of one hour after meal was as high as 98%, and the accuracy was 92% two hours after meal.

References

Ampuero S., Bosset J.O., 2003, The electronic nose applied to dairy products: a review, Sensors & Actuators B Chemical, 94(1), 1-12, DOI: 10.1016/S0925-4005(03)00321-6

Arshak K., Moore E., Lyons G.M., Harris J., Clifford S., 2013, A review of gas sensors employed in electronic nose applications, Sensor Review, 24(2), 181-198, DOI: 10.1108/02602280410525977

Berkel J.J.B.N.V., Dallinga J.W., Möller G.M., Godschalk R.W.L., Moonen E., Wouters E.F.M., 2008, Development of accurate classification method based on the analysis of volatile organic compounds from human exhaled air, Journal of Chromatography B, 861(1), 101-107, DOI: 10.1016/j.jchromb.2007.11.008

Chan H.P., Lewis C., Thomas P.S., 2009, Exhaled breath analysis: novel approach for early detection of lung cancer, Lung Cancer, 63(2), 164-168, DOI: 10.1016/j.lungcan.2008.05.020

Dragonieri S., Schot R., Mertens B.J., Le C.S., Gauw S.A., Spanevello A., 2007, An electronic nose in the discrimination of patients with asthma and controls, Journal of Allergy & Clinical Immunology, 120(4), 856-862, DOI: 10.1016/j.jaci.2007.05.043

Dutta R., Hines E.L., Gardner J.W., Kashwan K.R., Bhuyan M., 2003, Tea quality prediction using a tin oxide-based electronic nose: an artificial intelligence approach, Sensors & Actuators B Chemical, 94(2), 228-237.

Li Y., 2018, Study on spatial distribution characteristics of heavy metal chemical pollution in jiuzhaigou scenic area, Chemical Engineering Transactions, 66, 631-636, DOI:10.3303/CET1866106

Manolis A., 1983, The diagnostic potential of breath analysis, Clinical Chemistry, 29(1), 5-15.

Mazzatenta A., Pokorski M., Di G.C., 2013, Real-time breath analysis in type 2 diabetes patients during cognitive effort, Advances in Experimental Medicine & Biology, 788(4), 247.

Mueller D., Obermann M., Koeppen S., Kavuk I., Yoon M., Sack F., 2010, Electrically evoked nociceptive potentials for early detection of diabetic small-fiber neuropathy, European Journal of Neurology, 17(6), 834-841, DOI: 10.1111/j.1468-1331.2009.02938.x

Mutlu G., Garey K., Robbins R., Danziger L., Rubinstein I., 2001, Collection and analysis of exhaled breath condensate in humans, American Journal of Respiratory & Critical Care Medicine, 164(5), 731-737.

Risby T.H., 2006, Current status of clinical breath analysis, Applied Physics B, 85(2-3), 421-426, DOI: 10.1007/s00340-006-2280-4

Tonzetich J., Coil J.M., Ng W., 1991, Gas chromatographic method for trapping and detection of volatile organic compounds from human mouth air, Journal of Clinical Dentistry, 2(3), 79.

Wilson A.D., Baietto M., 2009, Applications and advances in electronic-nose technologies, Sensors, 9(7), 5099-148.

Wu L., Wang Q., Ma S., Yin Z., Xu J., Zhao L., 2018, Theoretical analysis and experimental research on constant current source of high stability semiconductor laser, Chemical Engineering Transactions, 66, 1297-1302, DOI:10.3303/CET1866217

Yu J.B., Byun H.G., So M.S., Huh J.S., 2005, Analysis of diabetic patient's breath with conducting polymer sensor array, Sensors & Actuators B Chemical, 108(1–2), 305-308, DOI: 10.1016/j.snb.2005.01.040

Zhi Y.F., Yuda S., Anderson V., Short L., Case C., Marwick T.H., 2003, Echocardiographic detection of early diabetic myocardial disease, Journal of the American College of Cardiology, 41(4), 611-617, DOI: 10.1016/S0735-1097(02)02869-3