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SMELL INDEX FOR INDOOR AIR QUALITY SYSTEM BASED ON MULTILAYER PERCEPTRON (MLP)

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Abstract

Indoor air quality index (IAQI) is developed to help users understand the effect of air pollutants to human's health, with respect to each band. It also gives an overall idea about the condition of air in the locations or rooms being measured. However, most of the IAQ indices presented by previous researchers in their works is calculated based on single pollutatant parameter only like carbon monoxide (CO) and sulfur dioxide (SO_2). Since smell is also part of indoor air contaminants, thus it is important to calculated the IAQ indices based on an array of pollutant parameters. This study proposes a smell index (SI) that can inform the user about the perception of smell presents either the smell is "Neutral", "Pleasant" or "Unpleasant". In contrast with the IAQI which generates its index based on single pollutant parameter, SI is generated based on an array of pollutant parameters. It generates the smell perceptions based on all pollutants input from six gas sensors, which are parts of an indoor air quality monitoring system (IAQMS). In order to classify the perception smell, multilayer perceptron (MLP) classifier with a back propagation learning algorithm has been used. The results show that the classifier has successfully classify the perception of smell for each pollutant present in indoor environment like ambient air, human activity, presence of chemical products, presence of food and beverage, and presence of fragrance. The model for smell classification which is used to produce smell index (SI) is assigned with the following weightage: "Pleasant" - 1, "Neutral" – 0 and "Unpleasant - 2". This SI is embedded to the IAQMS system.

Keywords: Smell index; Indoor air quality; Multi-layer perceptron;

1.0 INTRODUCTION

A good indoor air quality monitoring system (IAQMS) provides an indicator of the level of air quality (IAQ) to the users. The indicator may be offered in term of index, charts or symbols. The index, for example, is a numerical scale with color code which is divided into several specific ranges. It transforms the data collected on pollutions' concentrations into a meaningful index which can be easily comprehended by users [1]. Index has been widely used as a tool to communicate warning to the civilian about the level of air quality in outdoor environments. Now, the index system is being applied widely in indoor environments as well [2], [3], [4], [5]. However, most of the IAQ indices presented by previous researchers in their works is calculated based on single pollutatant parameter only like carbon monoxide (CO) and sulfur dioxide (SO_2). Since smell is also part of indoor air contaminants, thus it is important to calculated the IAQ indices based on an array of pollutant parameters.

The human sense of smell is a primary factor in the sensation of comfort. Olfaction as a sensory system brings awareness of the presence of airborne chemicals. Some smell which are inhaled contain chemicals that act as a stimulus or triggering unwanted reactions such as irritation to nose, eye and throat. Perception of smell and of irritation is unique to each person, and varies because of physical conditions or memory of past exposures to similar chemicals. A person's specific threshold before an smell becomes a nuisance depends also on the frequency, concentration, and duration of an odor.

This study includes smell as part of indoor air quality index (IAQI) calculation. In contrast with the IAQI which generates its index based on single pollutant parameter, SI is generated based on an array of pollutant parameters. For example, IAQI is determined based on single pollutant that gives the lowest rate [7]. SI, on the other hand, generates the smell perceptions based on all six pollutants input from six gas sensors, which are parts of an IAQMS in this study. The final result would be classified the smell as neutral, pleasant or unpleasant. Basically, smell can be categorized into 10 basic categories or clusters as shown in Table 1 below. It can be easily labeled as fragrant, sharp/pungent, chemical, sweet, fruity (non-citrus), fruity (citrus), toasted, minty and woody.

Table 1. Smell Categories.

No	Smells	Smell Sample	Perception of smell
1	Fragrant	Air freshener and perfumery, floral or herb Rosy smells	Pleasant Neutral Unpleasant
2	Sharp	Cigar smoke, pesticides, sour milk, and garlic	Strong Sickening
3	Chemical	Detergent, paint, gasoline, ink marker	
4	Sweet	Chocolate, vanilla and caramel	
5	Decayed	Rotten food (meat/fish), garbage and manure	
6	Fruity (Non-citrus)	All non-citrus fruits/alkaline (banana, watermelon)	
7	Fruity (Citrus)	Lemon, orange, pineapple and etc	
8	Toasted	Nuts	
9	Peppermint	Tea leaves and camphor	
10	Woody	Freshly cut grass and mushrooms	

In order to sense and measure the smell, this study uses an electronic nose (E-Nose) which was already developed for previous studies [8], [9], [10]. The development of E-Nose has been described in previous papers adopts an array of sensors including gas sensors, particle sensors and thermal sensors to detect and classify multiple pollutant parameters at a relatively low cost as compared to the professional sensing evices. It uses eight sensors to measure nine indoor air pollutants which are Oxygen (O2), Carbon Dioxide (CO2), Carbon Monoxide (CO), Ozone (O3), Nitrogen Dioxide (NO2), Volatile Organic Compounds (VOCs), Particulate Matter (PM), Temperature (Temp) and Relative Humidity (RH). E-Nose is an instrument that attempts to replicate the biological olfactory system. Unlike many other analytical techniques, an electronic nose does not try and separate all the chemical components within a sample, but it perceives the sample as a whole, creating a global fingerprint. It contains a number of components that replicate parts of the biological system as shown in Figure 1 below. For example, the smell that emanates from cigarette smoke has hundreds of different chemical components, but the biological olfactory system or E-Nose simply identifies the total chemical composition as cigarette smoke.

In an electronic nose, the gases emanating from cigarette smoke are delivered to an array of gas sensors (in this case the selected IAQ sensors). This sensor responds can be transformed to a chemical fingerprint in the processed signal stage. Neural network such as multilayer perceptron (MLP) can be used to differentiate between different chemical fingerprints (between fingerprints of cigarette, coffee and other sources). Each source that emits smell is assigned with the default smell perception. The cigarette smoke, for example, is assigned with unpleasant smell perception. The final output of neural network would be in terms of smell perception ("Pleasant", "Unpleasant" or "Neutral") which carry its own weightage.

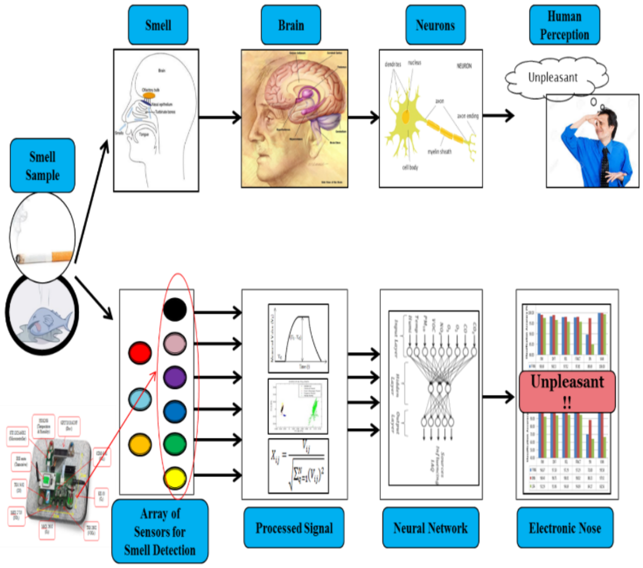

Fig. 1. E-nose based on biological olfactory system.

2.0 EXPERIMENTAL

There are certainly a lot of activities and conditions which could trigger smell or indoor air pollution (IAP) such as carpets and furnishings, cleaning products, office machines, construction activities, water-damaged building materials, perfumes, cigarette smoke, insects and outdoor pollutants. Although these smells are usually safe for human, they could be hazardous to human being especially people with respiratory-related problem and children, if their amount exceeded certain limits as proposed by the US EPA [11], [12]. For the purpose of this study, the sources of IAP are limited to five conditions that are commonly present in indoor environment: ambient air, human activity, presence of chemical products, presence of food and beverage, and presence of fragrance [13], [11], [14], [12]. All 5 sources have been categorized into three types of smell perceptions: "Neutral", "Pleasant" and "Unpleasant" as shown in Table 2 below.

Table 2. Smells samples.

No	Smells	Smell Sample	Smell Perception
1	Fragrance	Air Fresheners	Pleasant
2	Sharp	Cigarette smoke	Unpleasant
3	Chemical	Chemical cleaning product	Unpleasant
4	Decayed	Rotten cooked fish	Unpleasant
5	Natural Air	Ambient air	Neutral

3.0 RESULTS AND DISCUSSION

Multilayer Perceptron (MLP) is an interconnection of perceptron in which data and calculations flow in a single direction, from the input data to the outputs. The number of layers in a neural network is the number of layers of perceptron. The simplest neural network is one with a single input layer and an output layer of perceptron. The MLP uses the supervised learning method. In this research, the MLP using back propagation (BP) algorithm is used for identifying sources of pollutants influencing the IAQ. It is used since it is the standard classifier used in artificial neural network (ANN) for multiclass classification.

MLP is the most widely used tool in the field of ANN. Neural networks with a back propagation learning algorithm have started their history from the ideas presented by D.E. Rumelhart and J.L McClelland in 1986. The popularity of the usage is mainly due to its effective general method of training which can be applied in many applications, for example, in the forecasting and diagnosing [15]. A MLP is a network that contains three layers called input layer, an output layer and a hidden layer.

Generally, the network involves three stages of process, namely, the feed forward of input training pattern, the back propagation of the calculated error and lastly, the weight adjustment. Activations flow from the input layer through the hidden layer, then to the output layer. In order to classify perception of smell for those five sources of indoor air pollution, this study used the MLP which consists of three layers: input layer, hidden layer and output layer. As network architecture, a 3-layer perceptron model as shown in Figure 2 is used.

First input layer contains the input variables for the network that contains six neurons of IAQ parameters which are CO_2, CO, O_3, NO_2, O_2, and VOC. There is one hidden layer used and the numbers of hidden neurons were not fixed and were adjusted until the desired performance was achieved. The last layer of the model is the output layer which consists of 3 target outputs that represent three types of smell perception which is "Pleasant", "Neutral" and "Unpleasant". For classification process, 60% of all data are selected randomly to become the training set. A goal is set (in this case, mean square error (MSE) of 0.0001 has been chosen as the goal) and the training dataset is trained until the desired MSE is obtained.

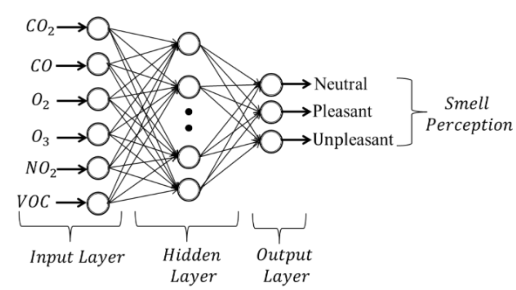

Fig. 2. Network architecture for smell perception.

MSE was used as the stopping criterion. Training was conducted with 10 trials until the MSE falls below 0.0001 or a maximum epoch limit of 1000 is reached. It is to ensure that the model is trained with minimum error iteration and not over trained. The learning rate and momentum factor are chosen based on experimental analysis. The number of hidden neurons is adjusted by the network to achieve this goal. The testing tolerance of the neural network model is chosen as 0.1. This value is the maximum allowable tolerance level for the testing. The detailed parameter for MLP training is given in Table 3. The hidden neurons are adjusted by increasing 3 for each trial. For example, to train the dataset for the condition of cigarette smoke, the data from all six IAQ parameters become the neurons for the input layer. Randomly, 60% of each IAQ parameter is selected to be the training set (60% out of 960 data for cigarette smoke). The training was repeated 10 trials and was conducted until the targeted MSE is reached or until a maximum epoch limit of 1000 is reached. This process is repeated with other four smell samples. In the end, the network would produce a model which is then tested against the 40% of the remaining data for all conditions (the testing set) in order to find the classification accuracy.

Table 3. Parameters for MLP training.

Training Parameter	Value
Sample • Number of samples used for training: 2880 • Number of samples used for testing: 1920 • Each sample: 960	4800
Input	6
Hidden neurons	Flexible
Output neurons	3
Performance	MSE
Goal	0.0001
Learning rate	0.01
Momentum constant	0.5

The model for smell classification which is used to produce smell index (SI) is assigned with the following weightage: "Pleasant" -1, "Neutral" – 0 and "Unpleasant". This SI then is embedded to the IAQMS system. The result for the network model along with the classification results is shown in Table 4 that used testing set of data sample. From Table 4, it can be observed that the model with network structure 9-9-3 and 9-15-3 gave the highest classification accuracy at 100%. However, the network structure of 9-9-3 is chosen since it required less hidden neurons compare with 9-15-3 network model.

Table 4. Performance of MLP for VAN feature.

Model Number	Model Structure	Classification Accuracy
1	9-3-3	99.48
2	9-6-3	99.79
3	9-9-3	100.00
4	9-12-3	99.79
5	9-15-3	100.00

The experiments have been conducted in three different environment settings: air-conditioned environment, present of air freshener and cigarette smoke. These three experiments are used to illustrate the overall functionality of prototype real-time monitoring system and SI determination. Figure 3 shows the result of SI for the three environments.

For the ambient environment, the graph is plotted for both conditions: air-conditioner "OFF" and air conditioner "ON". The result of SI shows the status of "Neutral" which means no smell presents in that environment. The second graph is for the presence of air freshener. The air freshener releases fragrance every 15 minutes. Before the air freshener starts to release the fragrance, the status for SI is "Neutral". Once the air freshener released the fragrance, the status of SI improved from "Neutral" to "Pleasant" which indicates the presence of VOCs in the room.

The third graph shows the environment for presence of cigarette smoke. A person is asked to smoke in the room for 10 minutes. Then, the window is opened to release the smoke from the room. Before the smoking activity took place, status for SI is "Neutral". When the person smoked a cigarette in the room, the status for SI is affected and changed from "Neutral" to "Unpleasant". When the window is opened to purge out the smoke, the SI does not change and stays in "Unpleasant" status due to remaining smoke residue in the room.

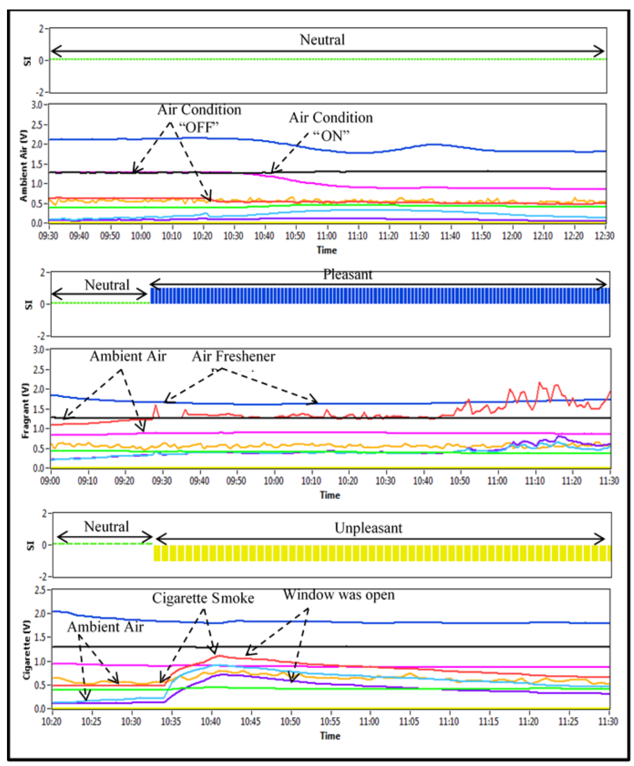

Fig. 3. Smell index for three conditions.

4.0 CONCLUSION

This study proposes a smell index (SI) based on MLP for indoor air quality monitoring system. This study includes smell as part of indoor air quality index (IAQI) calculation since smell is also part of indoor air contaminants. SI generates the smell perceptions based on all six pollutants input from six gas sensors of a pre-developed IAQMS. The final result would be classified by MLP as either the smell is "Neutral", "Pleasant" or "Unpleasant". The result of MLP classifier shows that the model with network structure 9-9-3 and 9-15-3 gave the highest classification accuracy at 100%. However, the network structure of 9-9-3 is chosen since it requires less hidden neurons compare with 9-15-3 network model. In order to test the model, several experiments have been conducted in three different environment settings – air-conditioned environment, present of air freshener and cigarette smoke. Based on the result of application of SI in controlled and real time environment, it is clear that the SI status changed according to simulation. Thus, it can alert and inform the user about the perception of smell so that can take action about the status.

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