

Classification of Domestic Burning Smell using Covariance k- Nearest Neighbour Algorithm for Early Fire Detection Application

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Fire is one of the most common hazards in households. It is the fifth leading unintentional cause of injury and death, behind motor vehicle crashes, falls, poisoning by solids or liquids, and drowning. It also ranks as the first cause of death for children under the age of 15 at home. Roughly, 80 percent of all fire deaths occur in places where people sleep, such as in homes, dormitories, barracks, or hotels. 74% of the deaths result from fires in homes with no smoke alarms or no working smoke alarms while surveys report that 96% of all homes have at least one smoke alarm. Nearly all home and other building fires are preventable. No fire is inevitable. Determination of burning smell is important because it can help in early fire detection and prevention. This preliminary study discusses the development of a fire sensing system that is not only capable of detecting fire in its early stage but also of classifying the fire based on the smell of the smoke in the environment. A domestic burning smell classification system for early fire detection application has been proposed using new covariance k-nearest neighbour (Ck-NN) algorithm. The experiments were performed on recorded smell samples from combustion of ten different commonly available domestic odour sources, including candle, joss sticks, air freshener, mosquito coil, newspaper, card board, plastic materials, Styrofoam and wood. All the experiments were done in a test chamber with humidity and temperature sensors. Portable Electronic Nose (PEN3) from AirSense Analytics is used as the measurement device. The smell source is placed 0.3m from the PEN3 and the time-series signal is measured for two minutes. The odour metrics consist of 66000 odour samples are modelled using Ck-NN algorithm. It is found that the average mean classification accuracy for the model is 99.63%.

1. Introduction

Fire detection is very significant and in many fields, a fire detection system is necessary. Basically, a fire is a chemical reaction in which a carbon based material (fuel), mixes with oxygen (usually as a component of air), and is heated to a point where flammable vapours are produced. These vapours can then come in contact with something that is hot enough to cause vapour ignition, and a resulting fire. In simple terms, something that can burn touches something that is hot, and a fire is produced. When the ignition source contacts the fuel, a fire can start. Following this contact, the typical accidental fire begins as a slow growth, smouldering process which may last from a few minutes to several hours. The duration of this "incipient" period is dependent on a variety of factors including fuel type, its physical arrangement, and quantity of available oxygen. During this period, heat generation increases, producing light to moderate volumes of smoke. The characteristic smell of smoke is usually the first indication that an incipient fire is underway. It is during this stage that early detection (either human or automatic), followed by a timely response by qualified fire emergency professionals, can control the fire before significant losses occur.



Figure 1: Commercial Fire Detector in Operation (Figaro Engineering, 2003)

Artificial sensing technology for odour is still a relatively new and challenging field and under intense research and implementation. For many decades, specific gas sensing detector with simple detection techniques has been used in various electrical devices and appliances to detect specific gases emanated in the process. In this paper, an artificial intelligence based algorithm has been successfully developed to classify various sources of domestic burning smells and nuisances. The algorithm not only classifies the same smell from different brands, but also the same smell at different concentration levels using different fire signatures. The smells detected are possibly the source of fire. Existing fire detector has limited capability to detect the fire at the early stage. The alarming system is only activated when greater smoke density or temperature is detected. Most of the fire detectors are only equipped with limited sensors and focusing on selected element of smell, making the probability of the detector creating false alarm is higher (Jose P. S. et al, 2012). Figure 1 shows the commercial fire detector in operation.

An electronic nose algorithm that can detect various smells of burning domestic material is proposed in the attempt to improvise the early fire detection in buildings. A test data was gathered to be trained and tested using an artificial neural network model. For initial testing, domestic burning materials such as mosquito coil, candle, joss sticks of different brands, newspapers, wood, plastic materials, Styrofoam and nuisance sources such as air freshener were tested. The tests were conducted in a temperature and humidity controlled chamber. The humidity and the temperature are monitored and recorded. Fresh air is mixed with the tested smell before being sucked into the electronic nose. The time-series signals from the ten metal oxide gas sensors in the electronic nose were recorded over a period of three minutes. The baseline trimming is performed to ensure that only the readings after the sensors stable are taken into consideration. The readings were at a sampling rate of five samples per seconds, compared to one sample per second sampling rate used in previous researches. Ten trials were done and the data collected were fed to the Ck-NN algorithm for classification. The best classification rate recorded is 99.98%, and the average mean classification rate for 50 repetitions is 99.63%. It produces an increase of 0.3% to 1.6% compared to the previous researches. The result also shows that Ck-NN can be utilised in electronic nose application as a reliable early fire detection system by sensing the changes in the air quality and comparing with the prior trained set of information.

The rest of the paper has been organised as follows: Section 2 narrates the literature reviews on related studies. In Section 3, the methodology of the research has been discussed. Section 4 shows the results and observations from the experiments. Finally, the paper is concluded in Section 5.

2. Literature Review

Fire cases in Malaysia are reported approximately 300 to 5000 cases per month, caused by various sources of fire, according to the source from 2012 statistics from Fire and Rescue Department of Malaysia. Almost all the cases of fire can be prevented if the existing fire detection system is improved with reliable hardware incorporated with effective algorithm for early fire detection and prevention. As mentioned in the section 1 of this paper, many researches were carried out for years in detecting the early fire using various technologies. The improvement of electronics, information and computer technology have contributed directly to the advancement of the early fire detection research for the last one decade. It is proven since there are many literatures published in this field for the last ten years.

The recent research conducted by a group of scientists from China, used the new method of smoke detection and classification based on a semi-supervised clustering model, which using an improved voting strategy to cluster types of smoke generated (Xu Y. et al, 2012). Similar to many other applications and researches, it is required to escalate the detection sensitivity, reduce the detection time, and raise the reliability to the system in times of uncertainty and nuisance. In simplified term, the detection system should detect the fire very early and can avoid the alarming due to the nuisance sources. The system should be tested to reliability in order to be implemented in remote, automatic fire prevention systems. Multi-criteria based detection technology is used in the mean of attaining both improvised real fire sensitivity and reduced vulnerability to the false alarm sources. The output measured from different gas sensors in an electronic nose is processed using a neural network pattern classification technique in an early fire detection alarming system (Jane H. et al, 2013).

Many stages are involved in the effective classification as the neural network pattern classification system is utilized in the multi- criteria or multi- sensor systems. The sensors convert the tested physical information to a numerical form of matrix. The sensor readings are defined in its respective axis in a multi-dimensional space. It can be interpreted as, in the case of ten gas sensors involved, ten axes will be created in the multi- dimensional space. Each fire and nuisance element will be symbolized as a point within this space based upon the sensor responses. Similar type of gases or nuisance will tend to group together in the space, gives each type of cluster to have its own mathematical boundaries. The mathematical boundaries enable the pattern clustering algorithms in the neural network to explain the pattern relationship in the data sets and thus, can be used to classify the fire and separate the nuisance sources (Banca C. et al, 2003; Susan L. et al, 2001; Sameer S. et al, 1996). This multi- sensor approach has been investigated with various degrees of success. Few researchers have compared and reported the improvement of multi- sensor approach over the existing threshold- based smoke detectors (M. Penza et al, 2001).

In recent times, electronic nose based indoor air monitoring and fire alarm system has become commercially available. This system, however, has not been adjusted to suiting specific environment and only available for general-purpose application. Precisely, the new systems available are only focused on the early fire detection and not really covering the wide range of nuisance source detection and rejection. Another limitation observed is the widely accepted standard such as the EN54 fire sources standard which limits the improvement to be made through test demonstration in fire detection sensitivity (Muller H., 2001). In this paper, the electronic nose based indoor air monitoring and fire alarm system is investigated for the commonly available fire and nuisance sources in Malaysia. The following section discusses about the methodology used for this research.

3. Methodology

The methodology in the research is divided into three main sections. These sections are discussed as follows.

3.1 Test Data Collection

Data is required to train and test the artificial neural network for maximum classification accuracy. Thus, a simple test data recording protocol is formulated to record the smell detected when the smell source is burning or smouldering. The experiments are conducted to record the smell sensing of ten burning and nuisance material, namely, Fumakilla mosquito coil, BT Lites candle, BIC joss stick, GLRS joss stick, card board, newspaper, plastic materials, Styrofoam, wood and air freshener, in the chamber. The data is recorded at a rate of five samples per second. Using 5 samples per second as the sampling rate is to ensure that more samples are available for the improved classification. The previous researches used one sample per second as the sampling rate.

Portable Electronic Nose (PEN3) from AirSense Analytics GmbH is used for this research as the measurement device. PEN3 is a small, fast and flexible identification system for gases and vapours. PEN3 is based on a ten metal oxide gas sensor array built into a small- volume measuring chamber. It has sensitive hot sensors, which can operate at extreme temperatures of 200 °C to 500 °C and sensor protection for long lifetime usage. It has a built-in vacuum pump at the flow rate, customizable between 10 ml/min to 400 ml/min. The sensor response time is less than 1 second, and it has a sensitivity of 0.1 ppm to 5 ppm for gases and organic solvents. The typical operating condition for the PEN3 is 0 °C to 45 °C for temperature and 5% to 95% for relative humidity. Charcoal filter is attached to the zero gas port as the air filter. The user has full access to all parameters of the instrument. The reading can be monitored through the measurement software, WinMuster allowing data acquisition and analysis. It can be communicated to the personal computer through RS232 or USB cable. PEN3 is designed according to the safety class compliant to EN292 Part 1 and 2, EN294, EN61010-1, EN1050, EN60204-1, EN 55011 G1 CB, EN50270 and EN6132 standards.

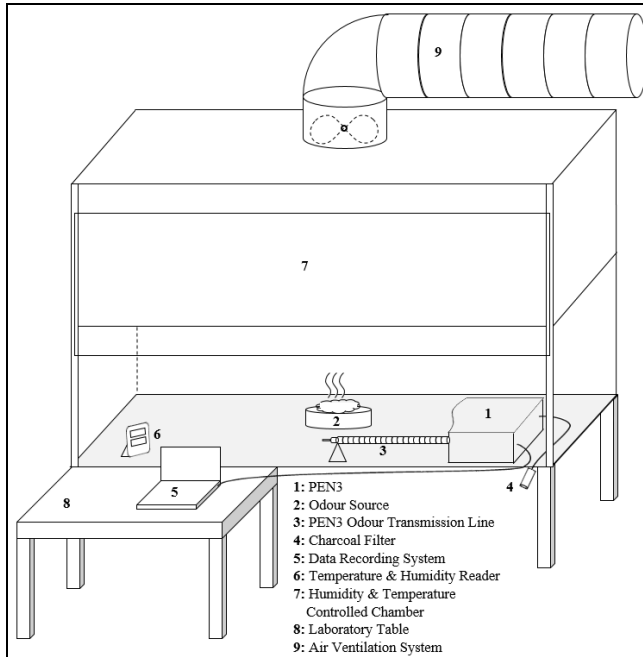


Figure 2: Experimental Setup for the Test Data Collection

Figure 2 shows the experimental setup for the test data collection. Prior to the data collection, the electronic nose is calibrated by allowing the clean air to rinse the metal oxide gas sensors from unwanted gas particles, which can contribute to reading error. Rinsing, in this context, means to make the sensor reading to return back to the base line (background value), by allowing the clean air to pass through the sensors. The humidity and the temperature were measured to ensure that, during the measurement, the values are within 20°C to 30°C and relative humidity of 30% to 40% respectively. The values were recorded for monitoring. The distance between the electronic nose and smell source is 0.3 meter. Each measurement was taken for three minutes. Each recording will only start two minutes after the burning process to ensure that the material is fully burned or smouldered. The ventilation fan in the chamber was also turned off to ensure that the smoke generated will not be sucked out. The raw data was saved in .nos format and has been converted to Microsoft Excel 2003 compliance file.

3.2 Signal Preprocessing

A simple preprocessing is performed on the recorded signals. Initially, the first minute of the recording for each sample is removed as the baseline trimming. This is due to the settling time needed by the sensors before the data measurement is stable. Based on the trial and error, it is observed that the settling time needed for this test to be 50 to 55 seconds. Thus, one minute is chosen as the settling time of the sensor reading.

The outlier values of the data set are removed prior to Ck-NN training. For each smell source, 6000 samples were collected for 10 repetitions. 6000 samples for the recorded fresh air are also included in this test as reference.

3.3 Covariance k- Nearest Neighbour Classifier

K-Nearest Neighbour (k-NN) is one of those algorithms that are very simple to understand but works incredibly well in practice. k-NN is a non parametric learning algorithm. When it is said a technique is non-parametric, it means that it does not make any assumptions on the underlying data distribution. This is pretty useful, as in the real world, most of the practical data does not obey the typical theoretical assumptions made (e.g. gaussian mixtures, linearly separable). Non-parametric algorithms like k-NN come to the rescue here.

A covariance matrix is a matrix whose element in the i, j position is the covariance between the i^{th} and j^{th} elements of a random vector. In a dataset of $m \times n$ sized, it has $m \times n$ sized covariance in a matrix form. In this research, covariance of the dataset is used as weights to be multiplied with the pre-processed dataset prior to the k-NN classification. This method is a new approach in imposing statistical feature in the classifier, replacing the Euclidean distance used standardly in k-NN algorithm. The covariance of the dataset is useful in discriminating the useful data from the invalid and redundant data.

The proposed k-NN consists of 10 inputs, which are the ten sensor values. Total of 66000 smell samples from ten smell sources are used. To compare the performance of the Ck-NN classifier, the samples were randomised and divided into eleven different data set of 6000 samples each prior to the classification. The next section discusses the results of the Ck-NN classification, and the observations made on the results.

4. Results and Discussions

Figure 4 shows the classification result of the domestic burning smell for 50 repetitions. From the figure, it can be observed that the average minimum classification accuracy recorded from all the dataset is 99.58%. The average maximum classification accuracy recorded from all the dataset is 99.91%. The average mean classification accuracy is observed to be 99.63%.

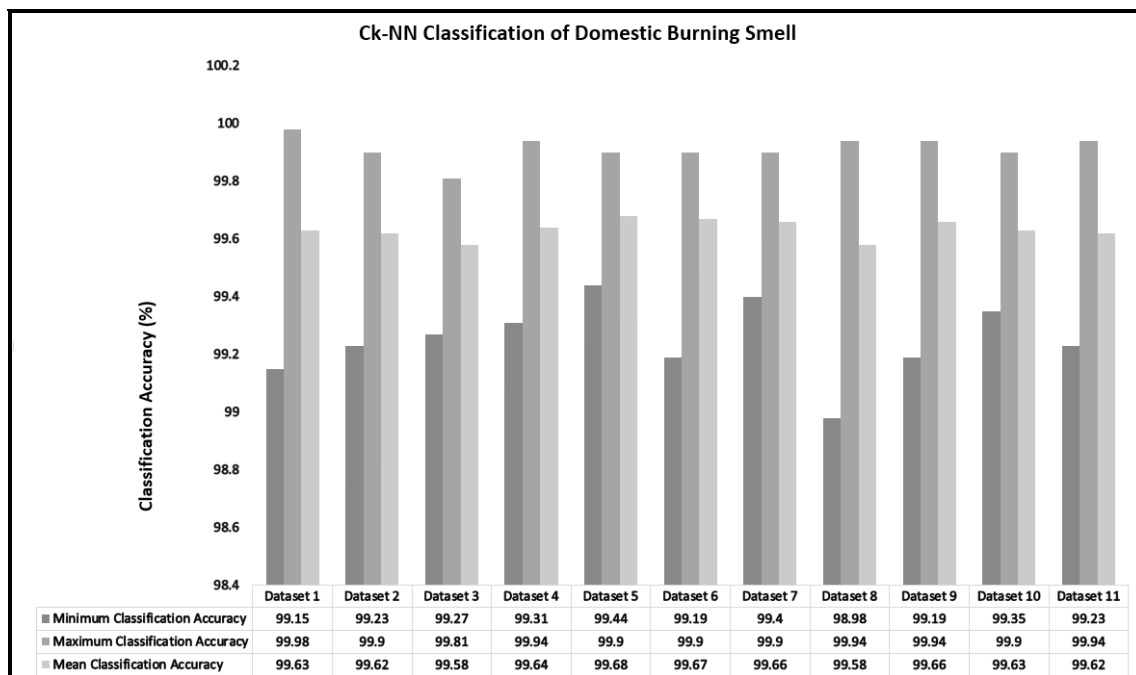


Figure 4: Ck-NN Classification Result of Domestic Burning Smell for 50 Repetitions

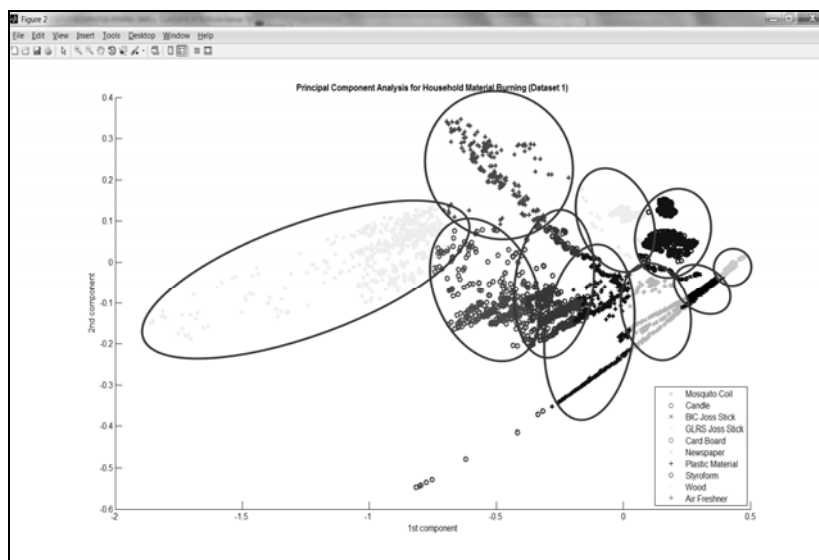


Figure 5: Principal Component Analysis on the Dataset 1

Based on the presented results, it can be clearly said that the Ck-NN classifier can classify the smells generated in the domestic successfully. The best classification accuracy recorded in this research is 99.98% from Dataset 1. All the datasets giving almost consistent classification accuracy, which indicates that the data is properly normalised and distributed. The accuracy of the classification can be further improved by performing common feature extraction and data reduction techniques, such as, Independent Component Analysis, statistical features, wavelet transforming and filtering and etc.

Figure 5 shows the Principal Component Analysis (PCA) on the Dataset 1. All the materials are consist of common household fire sources, building materials and nuisance sources. From the figure, it is observed that all the materials can be classified based on clusters with minimum misclassification. It indicates that all the household materials, regardless the material types and functions, have unique odour signature, which can be classified accurately by the classifier. The newspaper gives the most scattered data clustering while candle give least scattered clustering of data.

5. Conclusion

The research covers the concepts of digital signal processing techniques and artificial intelligence. Measurement device, AirSense Analytics Portable Electronic Nose (PEN3) was used to capture the smell produced in domestic burning. The signals were pre-processed before being fed to proposed Ck-NN. Based on the classification, it is observed that the classifier could classify the smells with the maximum accuracy of 99.68%. The PCA for the Dataset 1 is also shown. The model will be further improved by introducing more fire and nuisance sources and pre-process it with improved features in future research.

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