Multivariate Analysis of Temporal Features using Principal Component Analysis for Early Fire Detection in buildings

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***Abstract*—The usage of various effective algorithm will be helpful in early fire detection and prevention. In this paper, an in-building early fire detection algorithm has been proposed using Multivariate Analysis (MVA) using Principal Component Analysis. The experiments were performed on recorded smell samples from combustion of ten different commonly available household, including candle, joss sticks, air freshener, mosquito coil, newspaper, card board, plastic materials, Styrofoam and wood. All the experiments were done in a test room with humidity and temperature sensors. Portable Electronic Nose (PEN3) from Airsense Analytics is used as the measurement device. The smell source is placed 1.5m from the PEN3 and the time-series signal is measured for two minutes. The odour metrics is fed to the PCA for analysis. It is found that the MVA is able to cluster the odour sample accordingly with its first principal component of 92.74%.**

Keywords*— olfactory; fire detection; time series signal; classification; principal component

I. 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.

Analysis for odour is stills 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 [4]. 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 [9].

In this paper, a multivariate 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. Fig. 1 shows the commercial fire detector in operation.

Fig. 1. Commercial fire detector in operation [4]

Thus, 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 multivariate analysis. 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 room. The humidity and the temperature are monitored and recorded. The inlet of the electronic nose was put directly over the tested smell. 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 two 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 10 samples per seconds, compared to one sample per second sampling rate used in previous researches. Forty trials were done and the data collected were converted into temporal features for clustering using multivariate analyser. The best clustering rate recorded is 95%, and the average classification rate for 40 repetitions is 92.74%. The result also shows that multivariate analysis can be utilised in electronic nose application as a reliable early fire detection system by sensing the changes in the air quality.

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

II. BACKGROUND STUDIES

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. The problems in existing fire detection system is it has limited capability to detect the fire at the early stage, the alarming system is only activated when high smoke density or temperature is detected, most of the fire detectors are only equipped with limited sensors and focusing on selected element of smell, and the probability of the detector creating false alarm is higher.

As mentioned in the section I 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 [9]. It is proven since there are many literatures published in this field for the last ten years. The objective of this research is to improve the current fire detection systems. 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 [2]. The system should be tested to reliability in order to be implemented in remote, automatic fire prevention systems. Multivariate 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 an intelligent pattern classification technique in an early fire detection alarming system.

Many stages are involved in the effective classification as the 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 [3]. 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 analysis to explain the pattern relationship in the data sets and thus, can be used to classify the fire and separate the nuisance sources. 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 [4].

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. 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.

III. METHODOLOGY

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

A. Test Data Collection

Data is required to train and test the multivariate analyser for better clustering of data. Thus, a simple test data recording protocol is formulated to record the smell detected when the smell source is scorching 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 ten samples per second. Using ten samples per second as the sampling rate is to ensure that more samples are available for the improved clustering. 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. Fig. 2 shows the image of PEN3. 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 ºC to 500 ºC 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 ºC to 45 ºC 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.

Fig. 2. Portable Electronic Nose (PEN3) [9]

Figure 3 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 [4]. 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 20ºC to 30ºC and relative humidity of 30% to 40% respectively [5]. The values were recorded for monitoring. The distance between the electronic nose and smell source is 0.3 meter. Each measurement was taken for two minutes. Each recording will only start one minute 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.

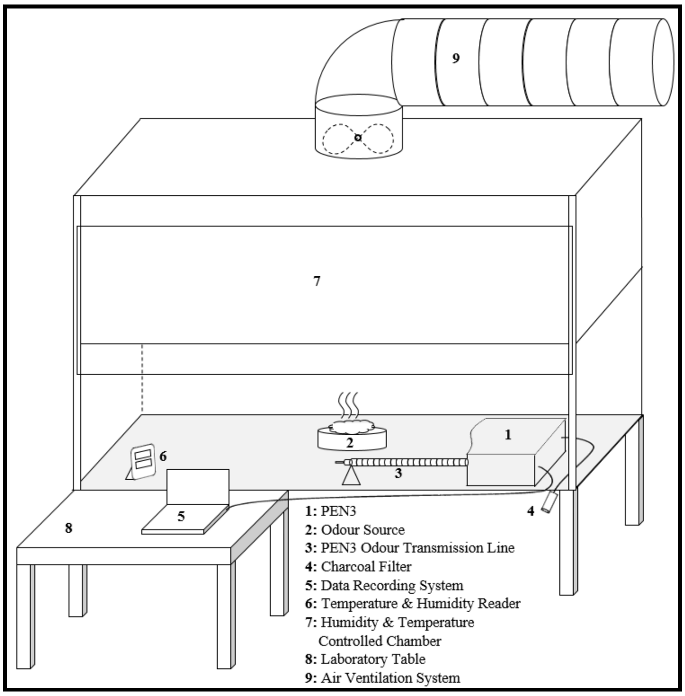

Fig. 3. Experimental Setup for Test Data Collection

B. 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 the analysis. For each smell source, 6000 samples were collected for 40 repetitions. 6000 samples for the recorded ambient air are also included in this test [6].

C. Principal Component Analysis

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to (uncorrelated with) the preceding components.

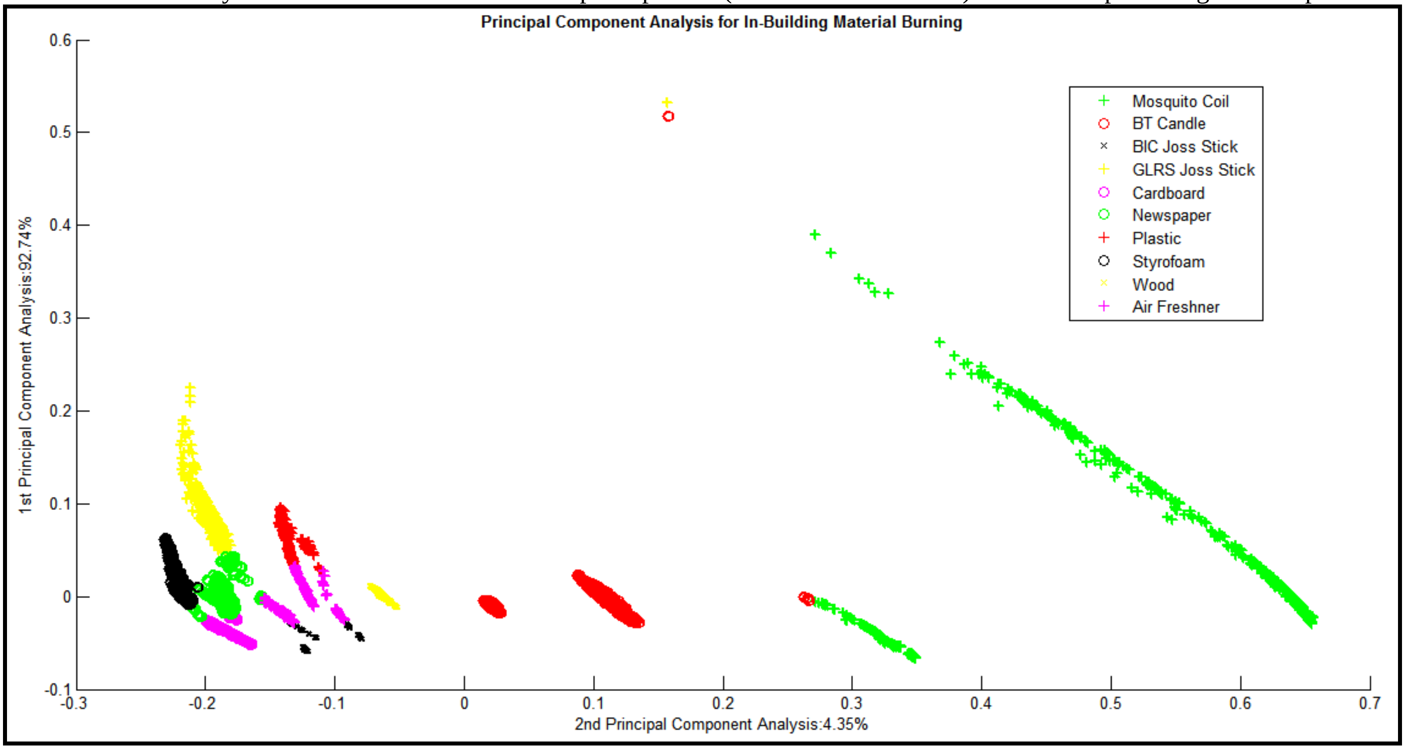

Fig. 4. Principal Component Analysis for Temporal Features

Principal components are guaranteed to be independent if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables [7,8,9].

PCA was invented in 1901 by Karl Pearson, as an analogue of the principal axes theorem in mechanics. It was later independently developed by Harold Hostelling in the 1930s. The method is mostly used as a tool in exploratory data analysis and for making predictive models. PCA can be done by eigenvalue decomposition of a data covariance (or correlation) matrix or singular value decomposition of a data matrix, usually after mean centering (and normalizing or using Z-scores) the data matrix for each attribute. The results of a PCA are usually discussed in terms of component scores, sometimes called factor scores (the transformed variable values corresponding to a particular data point), and loadings (the weight by which each standardized original variable should be multiplied to get the component score).

PCA is the simplest of the true eigenvector-based multivariate analysis. Often, its operation can be thought of as revealing the internal structure of the data in a way that best explains the variance in the data. If a multivariate dataset is visualised as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower-dimensional picture, a projection or "shadow" of this object when viewed from its most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced.

In this paper, PCA is used to dimensionally reduce the multivariate temporal features and represent the clustering of smell samples as two dimensional images.

IV. Result and Observation

Fig. 4 shows the PCA for temporal features in-building materials burning. From the figure, it can be seen that the odour sample were clustered accordingly in the PCA. The first principal component is 92.74% while the second principal component is 4.35%. The first principal component is higher since the dataset has high variances between the different types of materials. The Styrofoam has the best clustering rate since the distribution of the values is closer compared to other data. From the PCA plot also, we can see that the mosquito coil's values have a distributed pattern but still distinguished from other materials, which make them easily clustered. At the top of the figure, it can been observed that there are some values from candle and GLRS joss sticks which are distributed far from the other data. It might be because the values have high variance from other data but is considered outlier which not belongs to the specified class. 2.91% value which are not plotted in the PCA chart is assumed to be converted to other principal components which has lower and insignificant variances.

V. Conclusion

The multivariate analytic capability of the Principal Component Analysis is highly appreciated as a dimensional reduction and data selection method in various other applications. In this paper, PCA is used in clustering the dataset according to the types of smells generated in burning, yielding to 92.74% success rate. Thus, it can be concluded that the PCA can be used as a tool in clustering the smells generated from the in-building fires in early fire detection application. In future works, PCA will be used together with other intelligent classifiers for better classification accuracies.

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