Monitoring of Food Spoilage with Electronic Nose: Potential Applications for Smart Homes

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Abstract—**In ambient-assisted living environments, advanced sensors are used to detect potential problems that may affect the occupant. For a range of unsafe living conditions, characteristic odours arise that can provide early warning of a problem in the dwelling. In this paper, we investigate the concept of smell monitoring in the smart home environment, with particular attention paid to food spoilage. Using a commercially available electronic nose (e-nose) based on a metal-oxide sensor array, the odours associated with five common foods were captured over a seven day period. All foods were readily discriminated at the beginning of the measurement period. However, as the food spoiled, the odour profiles changed significantly. In several cases, the changes for a given food exhibited a clear trajectory in the PCA space. This preliminary work suggests that e-nose technology is a promising candidate for incorporation in the smart home. For widespread adoption, however, future e-nose development must continue to improve current shortcomings such as instability, user intervention, and high cost.**

Keywords-electronic nose; smart home; food spoilage; pattern classification

I. Introduction

Use of pervasive healthcare technologies in ambient assisted living environments (which includes the *smart home*) is becoming increasingly common. A smart home is defined as "a residential setting equipped with a set of advanced electronics, sensors and automated devices specifically designed for care delivery, remote monitoring, early detection of problems or emergency cases and promotion of residential safety and quality of life" [1]. Deployment of these technologies in a residential setting requires overcoming several real obstacles for general acceptance (particularly among the elderly), including ease of use and privacy considerations [2]. Despite this, inroads have been made. Technologies such as wearable vital sign monitors, bed sensors, and assistive lighting devices are now being used routinely in nursing homes [3].

TAFETA ("Technology Assisted Friendly Environment for the Third Age") is a research program currently underway at Carleton University and the Elizabeth Bruyère Research Institute in Ottawa, Canada. TAFETA brings together multi-disciplinary experts to develop smart technologies that help seniors live independently in safe, responsive environments [4]. In addition to those already mentioned, a variety of other assistive technologies are currently being investigated as part of the TAFETA project, such as smart grab bars, motion sensors, and microphone arrays [5,6].

As is the case with any private dwelling, routine events that occur in a smart home can lead to a variety of different odours in the ambient environment. A certain set of these (*e.g.* cooking and cleaning) would be considered normal and are expected to occur as a result of the occupant's day-to-day living. There are, however, other odours that can arise in this environment that are not so innocuous (*e.g.* garbage, urine, burning smell). When these types of smells occur, they may be indicative of a problem, but the occupant of a smart home is not always able to detect them (*e.g.* due to olfactory impairments or dementia) [7]. In this case, the occupant (or in cases where he or she does not have the capacity to act accordingly, a caregiver or family member) should be made aware of the situation in order to rectify the unsafe or unsanitary condition.

In order to minimize the risk of harm in these circumstances, various types of detectors and gas sensors can be installed in order to alert the occupant of a dangerous situation. Indeed, the smoke detector and the carbon monoxide detector are simple examples that have saved countless lives since their introduction [8]. These detector systems are by their nature application-specific, designed to detect a specific gas with high sensitivity and specificity. These sensors do not respond to, nor can they be trained to recognize, any other gasses or odours that may indicate a problem in a smart home.

Electronic nose (or *e-nose*) is a name given to a category of gas-sensing instruments that are designed to recognize odours from a wide range of possibilities. This is accomplished through the use of a sensor array with broad and partially overlapping sensitivities. With this arrangement, the individual sensors generate responses different from each other over a diverse set of odours. The result is a pattern which forms a signature of that smell. With training, the e-nose learns the pattern (called a *smellprint*) best representing each odour. Once trained, the e-nose can be used to identify unknown smells. In addition to the sensor array, an e-nose comprises a pattern recognition system (responsible for signal processing, feature extraction and training) and a sample handling component (which is needed to standardize the way in which the input is presented to the sensors) [9,10]. E-nose technology has matured in the last 10 years, and these instruments are gaining increased acceptance in industry. Successful applications include quality control and shelf life monitoring of food, beverages, and pharmaceuticals [11]. In addition, there has been a significant research and development effort to investigate their suitability in many other areas such as medical diagnosis [12], bacteria detection [13], and environmental monitoring [14].

Though the potential of e-noses has been proposed in the context of smart homes [5,15], its use has not been extensively explored. Adoption of ambient e-nose monitoring in the smart home will depend on the technology being unobtrusive, fully automated, cost-effective, and insensitive to normal environmental changes (*e.g.* temperature and humidity variations) to avoid the need for re-training [16]. In contrast, most current commercial electronic nose instruments are large and expensive, requiring a sophisticated sample handling apparatus and a highly pure carrier gas. A few portable e-noses exist (such as the Cyranose 320 (Smiths Detection, Pasadena, CA) [17] and the zNose (Electronic Sensor Technology, Newbury Park, CA) [18]), but they also have a relatively high cost and require significant user intervention for training, sniffing, and reading results. These are clearly not suitable for immediate deployment in the ambient-assisted living environment, and these practical limitations have been a real impediment for e-nose adoption in smart homes.

Recent research has demonstrated that many of the shortcomings of current industrial e-nose systems that make it presently unsuitable for smart homes will soon be overcome. The gas sensors are continually being miniaturized, making them more attractive for use in pervasive health monitoring environments. These new smaller sensors are now being fabricated using commodity technologies which will drastically lower manufacturing costs [19, 20]. Additionally, e-noses are now being fitted with wireless data transmission features [21]. Once this technology matures, it will be easier to aggregate the odour signals from multiple e-nose devices (positioned in different rooms) to a central odour monitoring station in the smart home.

Spoiled food is an odour category of particular importance in the smart home. Having the ability to detect food spoilage in this environment (and subsequently alerting the situation) can prevent the occupant (who may have impaired cognitive abilities and/or a weakened immune system) from suffering severe sickness due to ingestion, or it may also alert caretakers of a potential health issue. In this paper, we assess the capacity of a commercially available electronic nose to characterize the process of spoilage for a set of five common foods measured over several days. In so doing, we illustrate the potential uses and identify a number of practical problems that must be dealt with when e-nose devices become more pervasive in the smart homes of the future.

II. METHODS

A. Food Samples

In this study, we considered five common foods: homogenized milk (M), 18% cream (C), yoghurt (Y), eggs (E), and sour cream (S). These foods were purchased fresh from a grocery store and left out at room temperature over a period of 7 days to expedite the spoilage process. Groups of food samples were processed by the e-nose on five separate occasions during the experiment – on days 1 (fresh), 2, 3, 5, and 7. Figure 1 shows the difference in the appearance of the samples between the first and last days, illustrating clearly that spoilage has occurred by the end of the seventh day. On each of these days, the substance was mixed thoroughly, and then four 1mL samples from each of the categories were transferred by pipette into 10mL glass vials and capped. These samples were analyzed by the e-nose (see below) in alternating order (C,E,M,S,Y,C,E,M,S,Y…). A total of 100 samples were recorded, consisting of 4 samples/category (for each day) x 5 categories x 5 days.

(a)

(b)

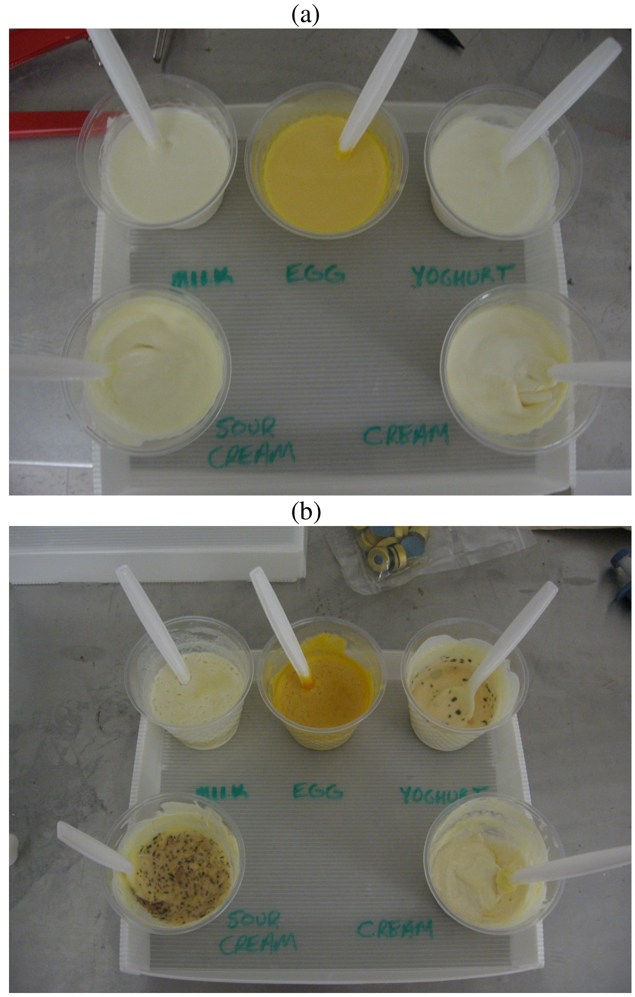


Figure 1 – Food samples used in e-nose experiments: (a) Day 1 and (b) Day 7.

B. Electronic Nose

The e-nose used to capture odour patterns consisted of an array of twelve metal oxide (MOS) sensors (AlphaMOS FOX, AlphaMOS, Toulouse, France [11]). The vial containing the sample was agitated and heated to 50^{o}C for 5min to concentrate the odour. A syringe was used to extract 2.0mL of headspace from the vial and then inject it into the sensor chamber. When this occurs, the MOS sensors respond by swelling or contracting by varying amounts. This changes their electrical conductivity over the duration of the gas sampling cycle in a manner that is slightly different from sensor to sensor. The sensor responses were recorded every 0.5 s for 2 minutes, giving a set of 12 response curves of conductivity *vs.* time (an example set is shown in Figure 2).

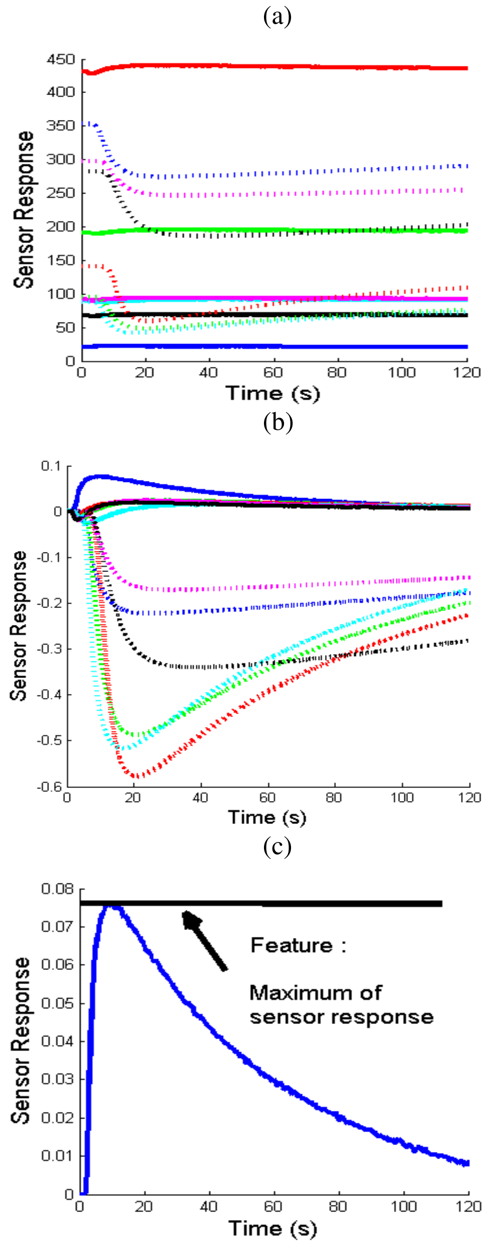


Figure 2 – (a) Raw sensor response curves for an arbitrary chosen cream sample, (b) Pre-processed sensor response curves, (c) feature extraction process (for a single arbitrary sensor).

C. Preprocessing and Feature Extraction

With the MOS, it was necessary to perform baseline manipulation in order to increase contrast and remove the effect of short-term baseline drift [22]. In our case, we used a fractional manipulation on the MOS data, defined as:

$$R_{i,preproc}(t) = \frac{R_i(t) - R_{i0}}{R_{i0}}$$

where $R_i(t)$ is the measured sensor response for sensor *i*, R_{i0} is the baseline response for sensor *i* (at $t=0$), and $R_{i,preproc}(t)$ is the scaled response retained for the following stages. The MOS response curves consist of 240 data points. Left unaltered, this would constitute an amount of information that is prohibitively large to use in a pattern recognition system. It is necessary to extract from this curve a more efficient representation for subsequent processing – ideally, so that a set of feature(s) retains the information essential for representing and differentiating between the different food categories. The most common approach (and the one we adopt here) is to represent the time series for each sensor with a single value. The maximum absolute value of $R_{i,preproc}(t)$, denoted m_i = max(abs($R_{i,preproc}(t)$)) was used as the feature of interest for each curve (see Figure 2(c)).

This process creates a vector for each sample *j*, $\mathbf{f}_j$, which consists of 12 elements. Each element represents the maximum feature from the sensor curve as described above:

$$\mathbf{f}_j = [m_{1,j} \quad m_{2,j} \quad m_{3,j} \quad \cdots \quad m_{12,j}\ ]$$

where $m_{i,\ j}$ is the i^{th} sensor's feature for sample *j*. Vector normalization was used to normalize the features for all samples, resulting in vectors $\hat{\mathbf{f}}_j$ in the direction of $\mathbf{f}_j$ with unity amplitude:

$$\hat{\mathbf{f}}_j = \frac{\mathbf{f}_j}{\|\mathbf{f}_j\|}$$

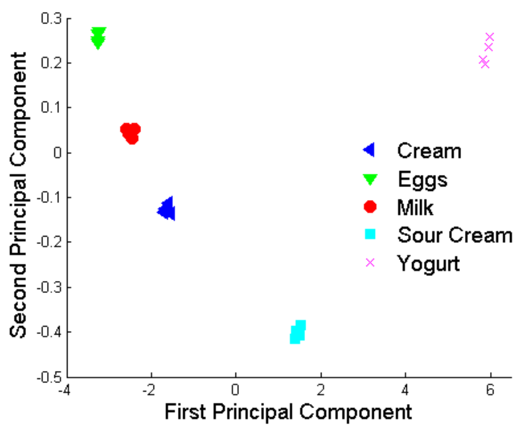
D. Dimensionality Reduction

Working with feature vectors in a high dimensional space is problematic by nature: a) the features are generally highly correlated (since the sensors have overlapping sensitivities), b) it is impossible to visualize the clusters, and c) the number of training samples required to cover this vector space is prohibitively large (it must grow exponentially with the dimension of the space). This is known as the *curse of dimensionality* and it is a significant impediment in machine learning systems [23]. E-nose systems generally perform a dimensionality reduction (DR) stage, wherein the dimension of the feature vector is decreased significantly. In this work, we used principal component analysis (PCA). PCA is an unsupervised DR method that calculates a new vector space from linear combinations of the original. In this new space, the basis vectors lie along the direction in which the original feature vectors displayed the greatest amount of scatter. PCA is generally used in exploratory data analysis, where the goal is to examine the generated e-nose patterns in a lower dimensional space. If separation between the various categories' samples can be demonstrated in the PCA space, we have a high degree of confidence that this can be further enhanced with the use of supervised DR methods (such as multiple discriminant analysis, MDA [23]). PCA was used to reduce the dimension of the feature vectors from twelve to two.

III. RESULTS

Figure 3 illustrates the capacity of the e-nose to discriminate between food samples *on a given day* throughout the measurement period. In these plots, each point denotes an individual food sample represented in the PCA space. On day 1 (fresh food, Figure 3(a)), the categories are very well separated, indicating that the measured odour signatures of each category are quite distinct from one another. However, at the end of the measurement period (day 7), the odour patterns of the cream, sour cream and yoghurt sample appear to come together. This is suggested visually by the significant amount of overlap between these groups' data points in Figure 3(b). Because overlap in the 2-dimensional PCA space does not unequivocally correspond to similarity of the measured patterns, though, we also computed the distance between the category centroids using the original 12-dimensional space. The results are shown in Table 1 and demonstrate that the degree of similarity between these pairs of sample categories increases from the beginning to the end of the experiment.

(a)



(b)

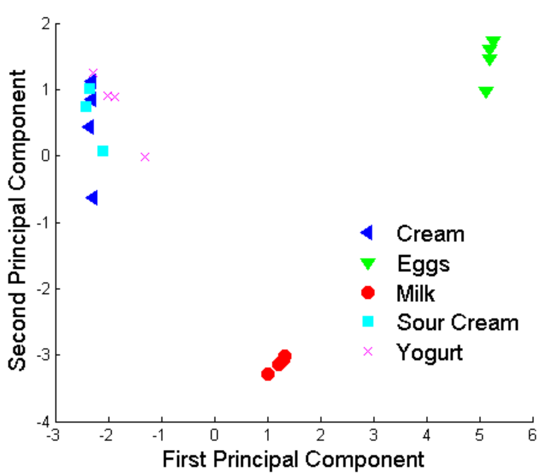


Figure 3 – PCA results for all food sample measurements on a given day: (a) Day 1, (b) Day 7. In each case, a different PCA projection is used.

TABLE I. DISTANCE BETWEEN CATEGORY CENTROIDS AT START AND END OF EXPERIMENT

Category	Distance Between Centroids (Day 1/Day 7)				
	Cream	**Eggs**	**Milk**	**Sour Cream**	**Yoghurt**
Cream	-	0.09 / 0.99	0.04 / 0.52	0.14 / 0.02	0.34 / 0.07
Eggs	0.09 / 0.99	-	0.05 / 0.62	0.24 / 0.99	0.43 / 0.95
Milk	0.04 / 0.52	0.05 / 0.62	-	0.19 / 0.52	0.39 / 0.49
Sour Cream	0.14 / 0.02	0.24 / 0.99	0.19 / 0.52	-	0.20 / 0.07
Yoghurt	0.34 / 0.07	0.43 / 0.95	0.39 / 0.49	0.20 / 0.07	-

We now turn our attention to the ability of the e-nose to measure food spoilage *over time*. With this goal, it is helpful to see how the odour patterns of the *same food* changes over the duration of the entire experiment. Figure 4 illustrates this behaviour for three of the food categories. In each of these cases, the individual clusters (representing the same food measured on different days) show minimal overlap. This indicates that the odour signatures of these foods (as measured by the e-nose) evolve quite differently as time progresses (*i.e.* as the food spoils). Moreover, when we track the centroids of the clusters over time (see the arrows in Figure 4), we see that these exhibit a relatively smooth trajectory in the PCA space as the food spoils. This is in agreement with our intuition – the food spoilage process is a gradual one (caused by, for example, continual bacterial growth in this host). As such, we would not expect these smellprints to show sudden discontinuities or jumps.

The results presented above show that as the experiment progressed, more within-category variability was evident. In Figure 4 (b) and (c), for instance, the cluster defining the Day 7 samples is much larger than those taken earlier. One possible explanation for this variation relates to the manner in which the samples were transferred to the vials. At the beginning of the experiment, all samples had a low viscosity. This made pipetting very easy – for these early samples, the volume transferred to the vial was very close to 1.0mL. Towards the seventh day, however, a number of the foods (particularly sour cream and yogurt) had thickened significantly. When pipetting this highly viscous substance, it was impossible to be confident that exactly 1.0mL was transferred. Furthermore, as time progressed, the foods were seen to grow moulds, develop crusts on the surface, and separate (Figure 1). In these cases, when the food is mixed before sampling, any remaining inhomogeneity in the sample will be manifested as variations in the e-nose responses. The resulting effect on the repeatability of the yogurt results is evident in Figure 5. For substances which remained less viscous (such as eggs), this effect was not seen (Figure 4(a)).

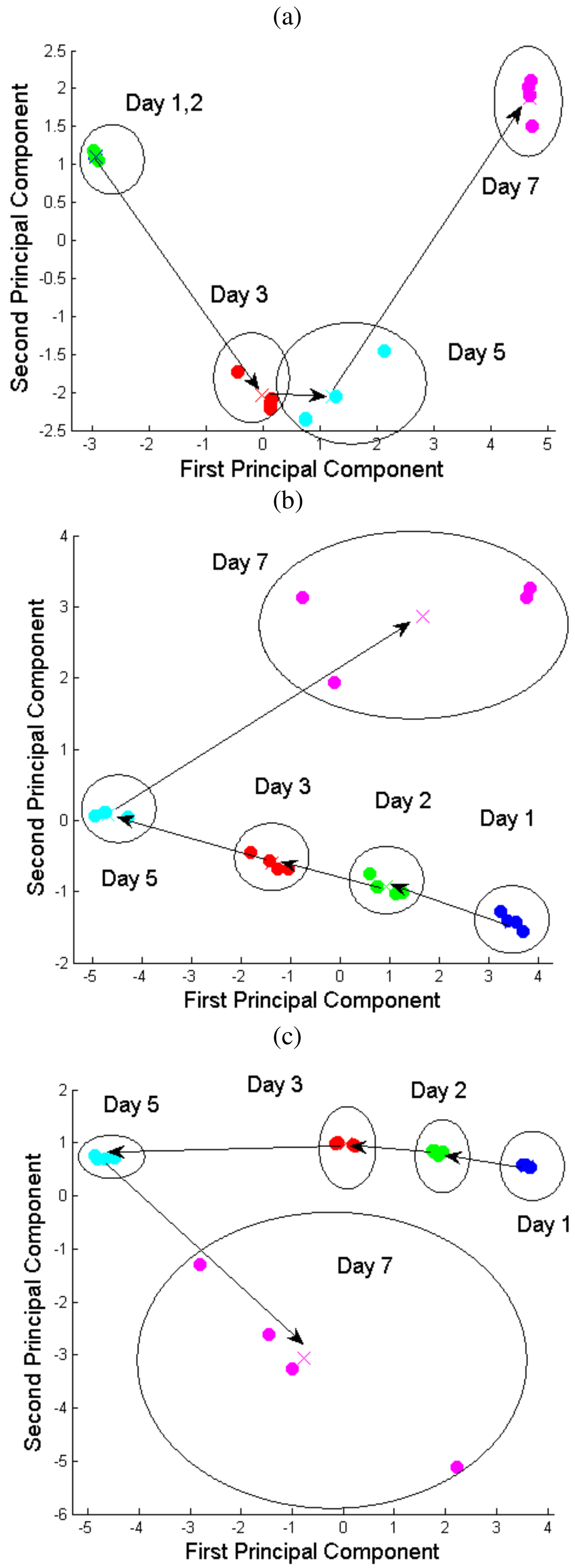


Figure 4 – PCA results for food samples measured throughout the entire experiment: (a) Eggs, (b) Sour Cream, (c) Yoghurt. Labels indicating the day of measurement are included for each cluster. Cluster centroids are marked with an "X" and the arrows show centroid progression with time.

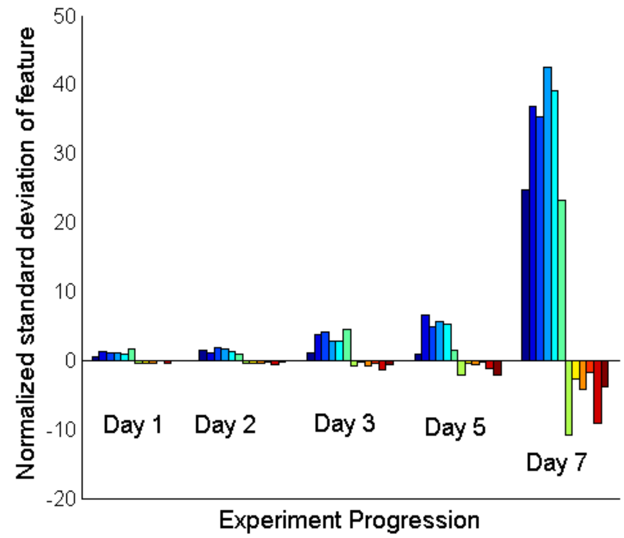


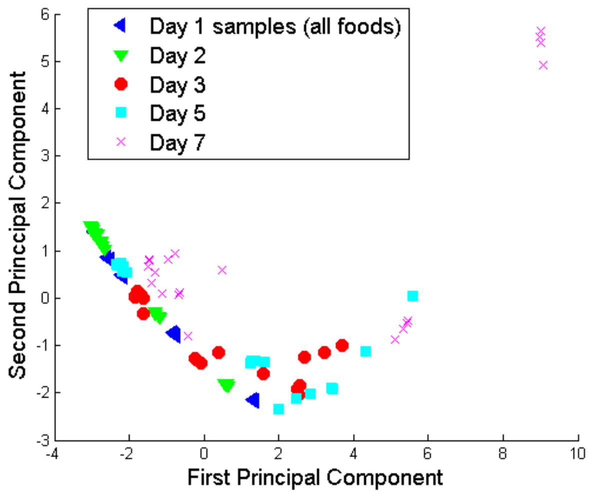
Figure 5 – Repeatability of measurements throughout experiment (yogurt). On each day, twelve bars are shown (one for each e-nose sensor). The height of each bar is a normalized measure of standard deviation, σ/μ, where μ and σ are respectively the mean and standard deviation of that sensor's extracted feature over all four samples processed on that day.

IV. DISCUSSION

There is a large literature which demonstrates the ability of e-noses to track food spoilage in very controlled environments [24-26]. In most of these papers, a single food is considered, and the e-nose sensor outputs are demonstrated to correlate with the severity of the mechanism which causes the spoilage (*e.g.* in [26], to the total viable counts of bacteria present in red meat are measured throughout the spoilage process (15 days), and the e-nose responses and its classification engine are trained against this "gold standard" bacteriological method). In this paper, we focused on a variety representative of common foods that would be present in a smart home. Additionally, we have not performed a bacteriological analysis of the spoiled foods. Instead, we have used simple time increments (essentially, the number of days at which the food has been left out at room temperature) as our measure for the degree of spoilage. This decision was deliberate, and allowed us to investigate the suitability of e-nose technology in this application domain with as simple an arrangement as possible. Further work in this area will certainly have to address the fact that since different foods spoil at different rates, a simple time measure of spoilage is not appropriate. Fuzzy methods are a potential candidate here and have been used successfully in e-nose studies [27]. Fuzzy methods assume that classification output category ranges are not mutually exclusive, but rather allow graded membership in a cluster.

Figure 6(a) illustrates that even with the small number of food categories studied in this paper, there does not appear to be a general "spoilage space" to which foods trend as they spoil. Despite this, we know that for wide variety of foods that have "gone off", they elicit odour responses which have a common trait – it smells generally very unpleasant to humans. Intuitively, then, it is plausible that by using supervised classification methods such as MDA and ANNs [23], better identification of spoilage over a wider range of foods can be achieved (see Figure 6(b)). This scenario ensures that, during training, the machine learning system is provided with not only the sensor responses to the sample, but also *a priori* knowledge of the degree of spoilage that the sample has undergone. It is then up to the supervised algorithms to learn the characteristics that all of the spoiled foods have in common, based on this labeled data

(a)



(b)

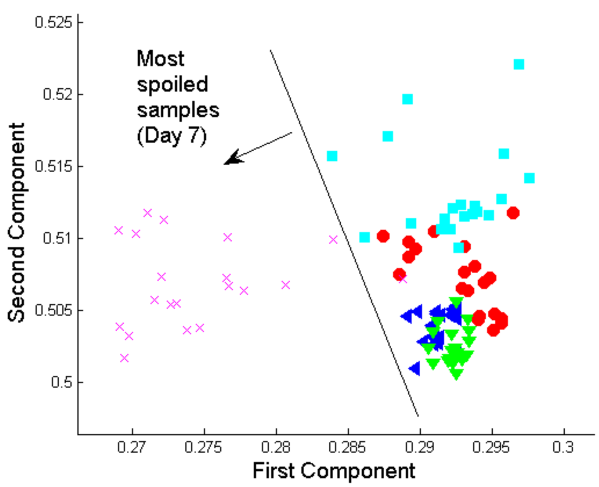


Figure 6 – Representation of all food samples – all days, all categories (100 samples) (a) PCA, (b) MDA. In the PCA plot, there is no trend towards a "spoilage" space as the experiment progresses (*e.g.* the Day 5/7 samples overlap with the earlier ones). However, when using MDA (a supervised DR method), the projection into the new space clearly separates the oldest (*i.e.* most spoiled) food samples.

In the future, it will be vital to keep abreast of research and industry developments in miniaturization, cost reduction, and usability of e-nose sensors. Those used in this study (while physically small) are packaged in a system which is prohibitively large and expensive for this application. Moreover, it will be important to continue to collect supplementary e-nose data for both: a) additional types of spoiled foods (*e.g.* meats, cheese, fish) and b) other odours from a wider category of interest in the smart home (*e.g.* burning food, garbage, hygiene-related). In doing so, we can continue to investigate the use of e-nose as an effective pervasive smart home monitoring technology.

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