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Identification of Food Spoilage in the Smart Home based on Neural and Fuzzy Processing of Odour Sensor Responses

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Abstract—**Adopting the use of real-time odour monitoring in the smart home has the potential to alert the occupant of unsafe or unsanitary conditions. In this paper, we measured (with a commercial metal-oxide sensor-based electronic nose) the odours of five household foods that had been left out at room temperature for a week to spoil. A multilayer perceptron (MLP) neural network was trained to recognize the age of the samples (a quantity related to the degree of spoilage). For four of these foods, median correlation coefficients (between target values and MLP outputs) of $R > 0.97$ were observed. Fuzzy C-means clustering (FCM) was applied to the evolving odour patterns of spoiling milk, which had been sampled more frequently (4h intervals for 7 days). The FCM results showed that both the freshest and oldest milk samples had a high degree of membership in "fresh" and "spoiled" clusters, respectively. In the future, as advancements in electronic nose development remove the present barriers to acceptance, signal processing methods like those explored in this paper can be incorporated into odour monitoring systems used in the smart home.**

I. Introduction

In any private dwelling, a wide variety of odours can arise. Generally, they result from the occupant's activities of daily living (ADLs), such as baking, cleaning, and washroom use; such odours are expected and are not indicative of any problem. Other odours, however, may be associated with problems of varying degree; prolonged garbage smell, the smell of food burning, or urine odour in the bedroom are simple examples of such odour events. In our work, we are particularly interested in using odour information to identify hazards in ambient-assisted living environments such as the *smart home*. 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]. The TAFETA project ("Technology Assisted Friendly Environment for the Third Age") brings together multi-disciplinary experts at Carleton University and the Elizabeth Bruyère Research Institute in Ottawa, Canada to develop smart technologies that help seniors live independently in safe, responsive environments [2]. The TAFETA smart home is the testing site for many of the ambient assistive technologies that are currently in development.

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We are currently investigating the potential use of odour monitoring systems in smart home environments. Olfactory impairments and dementia are more common in the elderly and may prevent them from recognizing "problem" odours and/or acting accordingly [3]. A fully automated odour detection system with sufficient sensitivity to identify a wide class of smells could be of great assistance to the resident of such a dwelling. With this system in place, the occupant (or alternately, a caregiver or family member) could be notified of a problematic situation and thereby address the unsafe or unsanitary condition which is causing it. An additional benefit of using an odour sensing system in this application is that it can be used for monitoring in a non-obtrusive manner (compared with *e.g.* video cameras).

Electronic nose (or *e-nose*) is the name given to a wide class of instruments capable of measuring odour information in different environments. An e-nose is a system that combines a gas sensor array (a wide variety of sensor modalities exist) with downstream signal processing and pattern recognition blocks [4]. The resulting system can be trained to associate a *smellprint* with various odours. Once trained, the e-nose can recognize smells as they arise and inform the user as to their origin. As a fast and relatively inexpensive analysis method, e-noses have been commercialized and have recently been widely adopted in the food industry (*e.g.* for quality control). Their use is also currently being investigated for food safety applications, such as discrimination of food borne pathogens [5].

In this paper, we restrict our attention to odours associated with spoilage of common household foods. Developing a method to identify spoiled food (based on its e-nose odour response) provides the ability to warn the occupant (who may have impaired cognitive abilities and/or a weakened immune system) of a potential health hazard and thereby avert illness due to ingestion. Using a commercial e-nose, we measured the changing odour signatures of five common foods during the spoilage process. This work expands on the work performed in [6], wherein we assessed the ability of this e-nose system to:

- distinguish between food sample categories *on a given day*, (separation in the principal component analysis (PCA) space was shown to degrade with spoilage), and

• measure a change in odour responses over time *for a given substance* (most foods demonstrated a clear trajectory in the PCA space as spoilage occurred).

In the present work, we introduce the use of artificial neural networks (ANN) and fuzzy clustering in the analysis. The use of a multilayer perceptron (MLP) allows us to measure the degree to which a neural network architecture is able to learn the evolving odour signatures associated with these foods (and thereby determine a spoilage measure from an unseen sample). In addition to the cohort of samples mentioned above, a further experiment was performed in which, for a single substance (milk): a) we collected a *much larger number of odour responses,* and b) sampling was performed at *regular intervals* (every 4 hours). For this experiment, we applied fuzzy C-means clustering and investigated its ability to automatically cluster the samples based on their odour (with no *a priori* knowledge of age).

II. METHODS

A. Electronic Nose

An e-nose consisting of 12 metal oxide (MOS) sensors was used to generate the raw odour patterns used for subsequent processing (AlphaMOS FOX, AlphaMOS, Toulouse, France [7]). Vials containing 1mL of each food sample were capped and then warmed to 50^{o}C for 5min to concentrate the odour in the vial. After this, 2.0mL of headspace was transferred (by syringe) to the sensor array. In the presence of the sample, the MOS sensors expand/contract and each one generates a conductivity *vs.* time response curve (see Figure 1). From this set of curves, the feature vector used to describe each sample was generated by: 1) performing a fractional baseline transformation on the sensor responses, 2) selecting from each transformed curve the maximum absolute value as the feature for that sensor, and 3) normalizing the resulting 12-dimensional vector to unity magnitude. A detailed description of the feature extraction process appears in [6].

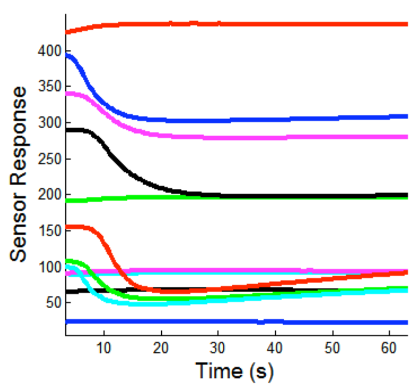

Fig. 1. Raw e-nose sensor responses for an arbitrary milk sample. There is one curve for each of the 12 sensors.

B. Spoiled Food Samples – Multi-category

Our initial experiment investigated the spoilage odours of five different foods. Fresh cream, eggs, milk, sour cream and yoghurt were purchased from a grocery store and left out at room temperature for a week to spoil. On days 1 (fresh, day of purchase), 2, 3, 5, and 7, four separate 1mL replicates of each category were sniffed by the e-nose in alternating order. Prior to e-nose processing, each of the foods was blended to ensure uniform consistency.

C. Spoiled Food Samples – Single-category

Further to the above, we performed an additional experiment that considered only a single food category (milk). Restricting the experiment to a single substance allowed us to perform more frequent, regular sampling of the substance over time. The time interval between sniffs for this experiment was 4h, and the milk was left out to spoil for 7 days (giving a total of 43 samples).

D. Artificial Neural Networks (ANN)

A back-propagation MLP was used to correlate the e-nose sensor responses with the degree of spoilage. In this work, we used a simple approach – the training targets (value of the single output node) for each food sample were linearly related to the amount of time that it had been left out to spoil. The target for fresh (Day 1) samples was set to zero; for the most spoiled samples (Day 7) the target was 1.0. The MLP used one hidden layer comprising 10 neurons, and the input layer consisted of 12 neurons (one for each e-nose sensor). The Matlab Neural Network Toolbox numerical computing environment was used (The Mathworks, Natick, MA) [8]. The transfer function "tansig" was used for the hidden layer, and "purelin" was used in the output layer. The input patterns were divided randomly into training, validation, and test sets (using 60%, 20%, and 20% of the data respectively) in order to avoid overtraining. Network training employed the Levenberg-Marquardt backpropagation algorithm until an MSE target of less than 10^{-6} was achieved, or the validation set error increased.

E. Fuzzy C Means (FCM) clustering

In the above analysis, we use time (specifically, the number of days at which the food has been left out at room temperature) as our measure of the degree of food spoilage. While simplifying the analysis, this assumption does not consider that: a) different foods will spoil at different rates, and b) any numerical measure of spoilage assigned without having performed a bacteriological analysis (*e.g.* colony counts) of the spoiled foods should be used cautiously. These observations suggest the use of fuzzy methods, which assume that the output categories are not mutually exclusive (Day 1, Day 2, etc.). Rather, each sample receives a *graded* membership in each cluster, typically represented with a scalar u between 0 and 1.

Fuzzy C-means (FCM) clustering (which has previously been used with success in e-nose analysis [9,10]) allows each of the sample patterns to have an association with *multiple clusters* instead of belonging to a single category exclusively. The membership matrix U represents this level of "belongingness" of an input pattern to a cluster. FCM clustering is performed as follows (see [11] for details):

1. Select the number of clusters, C, initialize the cluster centers (randomly), and assign points randomly to these clusters.
2. (Re-)compute the cluster centroids.
3. Compute u_{ic}, the "degree of belonging" of each data point i in cluster c, based on the distances of the data points to the newly computed cluster centers.
4. Repeat steps 2 and 3 until the incremental changes are below a predefined threshold.

III. RESULTS

A. Spoiled Food Samples – Multi-category

Figure 2 presents a regression analysis showing (for an arbitrary network trained as described above) the MLP outputs along with the specified targets for these input patterns (the data in this plot are shown for yoghurt samples only). The measured correlation coefficient ($R > 0.99$) demonstrates that this particular ANN architecture was able to learn the changing odour patterns as spoilage occurred.

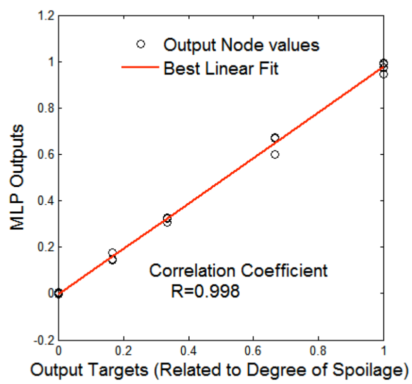

Fig. 2. Results of regression analysis comparing the sample age - related to degree of spoilage - (target value, on the horizontal axis) with that computed by the MLP (vertical axis). The red line and high R value indicate a very good linear fit.

Because a *single* trained MLP is sensitive to the randomly selected initial network weights, we repeated 100 training iterations to assess the robustness of this network architecture in this respect. Table 1 shows (for all food categories) the mean, median, and standard deviation of the computed R values over all 100 iterations. Clearly, the ANN is better able to track the spoilage of certain categories of foods (*e.g.* yoghurt) than others (*e.g.* cream).

Sample Type	Mean R	Std Dev R	Median R
Cream	0.822	0.238	0.893
Eggs	0.949	0.191	0.978
Milk	0.965	0.0367	0.976
Sour Cream	0.933	0.197	0.989
Yoghurt	0.979	0.0584	0.996

Table 1. Mean, standard deviation, and median of correlation coefficients over 100 iterations of MLP training for five food categories.

B. Spoiled Food Samples – Single-category

We now turn our attention to the experiment that provided *regular sampling* (interval = 4h) of a single substance, milk. Figure 3 shows the results of applying PCA analysis to the feature vectors obtained during the week-long spoilage process. While the fresher samples (*e.g.* days 1-2) cluster tightly in the PCA space, a distinct increase in variability of the sensors can be seen to emerge during the third day, and remains throughout the rest of the process.

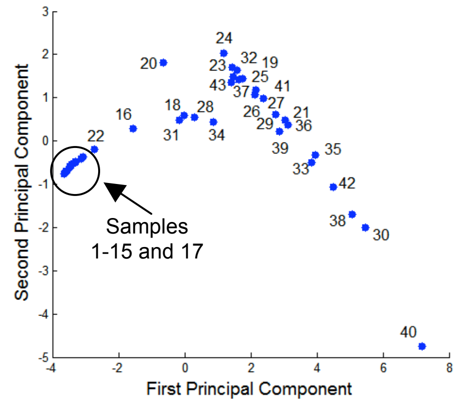

Fig. 3. Plot of first and second principal components, for milk sampled for one week at 4h intervals. The sample number next to each point represents the chronological sequence (*i.e.* sample #1 taken at $t = 0$h, sample #2 taken at $t = 4$h, sample #3 taken at $t = 8$h, *etc.*).

This sudden jump in the complexity of the sensor responses to milk resulted in training problems when the exact same ANN architecture as described above was used on these samples. Figure 4 shows a regression analysis of MLP outputs along with the specified targets for these input patterns.

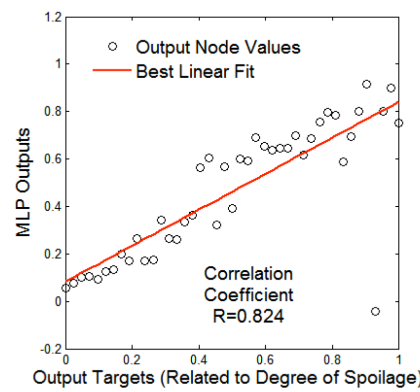

Fig. 4. Results of regression analysis comparing the sample age - related to degree of spoilage - (target value, on the horizontal axis) with that computed by the MLP (vertical axis). Notice the difference in sampling in this plot (regular 4h intervals) vs. Fig 2.

When trained over 100 iterations, the mean/std dev/median R value was, respectively, 0.882/0.128/0.911.

As an alternative to ANNs, FCM was applied to this input data with results shown in Figure 5. The memberships for each sample u_{ic} in each cluster are indicated on the left (spoiled) and right (fresh) axes labels. In this plot, we specified $C = 2$, which corresponded to the simplest approach (one cluster for fresher foods, the other for spoiled foods).

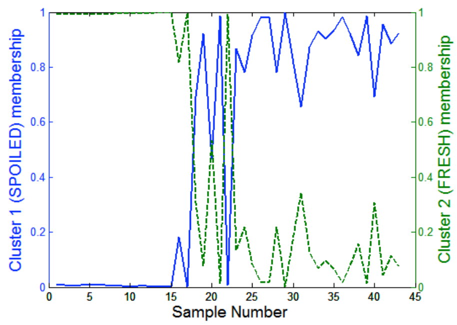

Fig. 5. FCM results, C = 2. On the horizontal axis, sample number represents the chronological sequence (*i.e.* sample #1 taken at t = 0h, sample #2 taken at t = 4h, sample #3 taken at t = 8h, *etc.*). The vertical axis on the right indicates degree of membership in FRESH cluster, on the left indicates degree of membership in SPOILED cluster.

It can be seen from this plot that the fresher milk (*e.g.* from the first 2-3 days, samples 1-15) have a high degree of membership (u > 0.95) in the "Fresh" cluster. Likewise, the oldest milk (from days 5-7, samples 24-43) have been associated with the "Spoiled" cluster, though not as prominently (u > 0.65). The remaining samples (those processed mid-week) do not as a group consistently associate with either of the clusters.

IV. DISCUSSION

The work described herein is intended to continue our evaluation as to whether currently available e-nose technology has the potential to recognize various olfactory events in the smart home (we focused on food spoilage in this paper and in [6]). The e-nose's ability to detect food contamination has been demonstrated in the literature (*e.g.* in [12]), but this has generally been done for a single type of food, in conjunction with a detailed analysis of the spoilage process (*e.g.* bacteriological methods). We opted instead to investigate the odour patterns for a *variety* of foods while not considering the underlying mechanisms. Future work in this area will add to this "library" of odours with other food types (*e.g.* meat, vegetables) as well as other groups of odours relevant to the smart home (*e.g.* garbage, bathroom).

Refinements to our signal processing and pattern recognition methods are warranted. For example, the ANN architecture could potentially be optimized in many respects, (*e.g.* including an increased number of hidden nodes, using alternative training methods or other network architectures). Another option would combine the dimensionality reduction techniques we have already investigated (such as PCA and MDA, described in [6]) *in concert with* the neural and fuzzy methods described herein. It is important to stress that FCM is an *unsupervised* clustering method, which in our work appears to have found inherent differences in the food odours based on the data itself, and *not* on *a priori* knowledge of the amount of spoilage. However, while FCM does effectively cluster both the freshest and oldest foods, further work should investigate why this method did not give a smoother transition between cluster membership results during spoilage. These efforts should be done with a largely increased number of samples collected at different times in order to increase confidence in the robustness and statistical validity of the system.

For a number of reasons (such as size, cost, and sample preparation), the commercial e-nose used in this study would not be suitable in a smart home environment. However, there is a trend in the e-nose industry towards instrument miniaturization which may make this option more appealing in the near future. Other relevant research activities include improvements in the e-nose's ability to monitor ambient air [13], and wireless operation with associated networking [14]. The latter would be important for aggregation of odour information from an array of e-noses deployed in a smart home.

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