AUGMENTING HUMAN ODOR ASSESSMENTS OF CABIN AIR QUALITY OF AUTOMOBILES BY INSTRUMENTAL MEASUREMENTS

HT Nagle[1], R. Gutierrez-Osuna[2], KS Suslick[3], K. Persaud[4], J. Covington[5], RD. Hodges[5], G. Luckey[6]
J. Crowell[6] and SS. Schiffman[1]

[1]NC State Univ., [2]Texas A&M Univ., [3]Univ. Illinois Urbana Champaign, [4]Univ. Manchester, [5]Univ. Warwick, [6]Hyundai Motor Group

ABSTRACT

Four commercial e-nose instruments (Multisensor Systems, Alpha MOS, iSense, and Nordic Sensors Technologies) and a trained human panel tested cabin odors generated by heat cycling four new automobiles. Odor samples were collected at Hyundai Motor Group (HMG) and express-shipped to four university partners for analysis by an aggregate of 155 gas sensors. Sensor responses were combined into a single dataset, from which models were developed to predict the human panel's odor evaluations based upon each instrument alone, and upon the instruments all acting together. The best performing sensors and instruments were identified. The best performance overall was a hybrid instrument composed of five sensors from three different commercial devices.

Index terms– Human panel, odor assessment, electronic nose

1. INTRODUCTION & BACKGROUND

In prior work [1], we showed that an electronic nose (e-nose) may be used to replace a human panel for the evaluation of odors from animal confinement facilities. In this project, we extend those concepts to automobile interior odors. Odors in new vehicle interiors arise from the out-gassing of compounds from leather, plastic, carpet, vinyls, paint, and glues. Human panels and electronic instruments (including GC/MS, MOSFET and MOS sensors, and a MEMS sensor array) have been used previously in a limited number of studies to evaluate cabin air odors from automobiles with mixed results [2-5]. In this study, we evaluated four commercial instruments with a combined total of 155 gas sensors for their ability to complement or replace human odor assessments of automobile cabin air odor quality within HMG vehicles.

2. METHODS

2.1 Sample collection at HMG

All data were collected in an environmental test chamber at HMG using company standards, under which the vehicle doors are open for 30 minutes (20 ± 5°C, 60% RH), HVAC set to recirculate, doors are then closed and the inside temperature raised over an hour period to 80°C at passenger nose level and maintained at this temperature for two hours, and then forcedly cooled over one and one-half hours to 25 ± 2°C. Human panelists (N=4) then entered the vehicles and recorded their ratings. Vacuum pumps were used to pull odor samples through Tenax absorbent material in glass tubes. These concentrated samples were refrigerated and sent by express carrier to Univ. of Ill. Urbana Champaign (UIUC), Univ. of Warwick (UWAR), and NC State Univ. (NCSU) for analysis. In parallel with the Tenax sample collection, solid-phase micro-extraction (SPME) fibers were also used to concentrate odorants; these samples were refrigerated and shipped by express carrier to Univ. Manchester (UMAN) for analysis.

2.2 Sample processing

UIUC. Forty eight Tenax samples were examined by a hand-held iSense colorimetric e-nose system that exposes an array of sensing spots on a flat array. The spots change colors in the presence of VOCs. A camera scans the spots and creates a feature vector for data analysis. An array of 108 sensor spots was exposed to a sample for 10 min during a test run. Hierarchical cluster analysis was used to group data, and all the samples except one fell nicely into their respective clusters, which suggests a good degree of selectivity and repeatability.

UWAR. Odor samples were evaluated with an Alpha MOS Fox 4000 instrument with 17 MOS sensors. Twenty four Tenax samples were removed from the glass tubes and placed inside a 10 ml sample vial. The vials were purged with nitrogen, sealed with a high temperature lid, heated, and maintained at 320°C for 20 minutes. An autosampler then injected 1.5 ml from the vial at 100°C into the instrument. We were not able to provide enough samples to enable this instrument to differentiate vehicle samples.

NCSU. Samples were evaluated with the Nordic Sensor Technology NST 3320 that employs an array of 12 MOS and 10 MOSFET gas sensors. Sixteen Tenax samples were removed from the glass tubes and placed inside 30 ml sample vials. The vials were then sealed with a membrane lid, and heated and maintained at 60°C during analysis. Sensor readings were taken every second and both the sensor's response and recovery waveforms were recorded. The NST 3320 could clearly differentiate between hot and cool vehicles. Clusters also differentiated for the hot vehicles, but not for the cool.

UMAN. The Multisensor Systems unit has 8 MOS sensors. Concentrated samples on 12 SPME fibers were automatically inserted into the sensor head by a drive unit. The system automatically recorded the baseline (without fiber) for 10 sec, and then drove the fibers into the sensor chamber for thermal desorption. The sensor signals were then recorded for three minutes followed by a cleaning cycle. Normalized patterns between 50-100 sec from each sample were used as input data into principal components analysis (PCA). The PCA plot easily differentiated between the different models of hot and cool vehicles under test.

Data Integration. The sensory data from UIUC, UWAR, NCSU, and UMAN were combined into a single database at Texas A&M University. A mathematical description of the problem for this feasibility study follows. Represent the human panel olfactory ratings by matrix Y whose dimensions are 8×3. The first is the number of vehicle tests (four vehicles tested at two temperatures); the second, the number of rating scales (Odor Intensity, Irritation Intensity, and Pleasantness). Each entry in Y is the median of the ratings from the four human panelists. Represent the instrument data by matrix X whose dimensions are $8\times D$. Eight is the number of vehicle tests, and D is the number of sensors for the different instruments. Each row in X is associated with one row in Y (many-to-one mappings). Consider the following equations:

$$\hat{Y} = XW \tag{1}$$

$$W^{*} = (X^{T}X)^{-1}X^{T}Y \tag{2}$$

$$W^{*} = \left((1-\varepsilon)X^{T}X + \varepsilon\frac{tr(X^{T}X)}{D}I\right)^{-1}X^{T}Y \tag{3}$$

Equation (1) illustrates that we want to find a matrix W that

allows us to predict the human panel ratings matrix $\hat{Y}$ (an estimate of Y) from instrument measurements collected in matrix X. The optimal matrix W (denoted W^*) is given in (2). To compensate for co-linearity in X, we introduce a regularization term ε in (3), which is found through cross validation.

3. RESULTS & DISCUSSION

3.1 Correlation coefficients and signal to noise ratio (SNR)

To evaluate the instruments, we used 70% of the data to determine the regression matrix W^*, then tested on the remaining 30% of the data. We then computed coefficients ρ as a measure of the correlation between the ground-truth olfactory ratings Y and their predictions $\hat{Y} = XW^*$. From these, we computed the signal-to-noise ratio (SNR) as:

$$SNR = std(Y) \Big/ \sqrt{\left\| Y - \hat{Y} \right\|^2} \qquad (4)$$

3.2 Which sensors are best?

To answer this question, we merged the four datasets and performed stepwise forward regression (SFR). First, we transformed the raw sensor data of each instrument according to its optimal preprocessing method: steady state x_∞ for UIUC and UMAN, and x_{max}/x_0 for UWAR and NCSU. Then, we merged replicate 1 of all the instruments into one large feature vector. This created a sparse dataset (8 vehicle tests × 155 sensors). To select sensor s_i, we split the data 70/30 and built a regression model in a SFR fashion. At each step, we repeated the split and regression model computation 56 times (with 8 vehicle tests there are approximately $C_3^8 = (8 \times 7 \times 6)/(3 \times 2) = 56$ possible 70/30 splits) and selected s_i as the best on average of the 56 trials based on a single figure of merit:

$$\bar{\rho} \times \overline{SNR} = \left[\frac{\rho_1 + \rho_2 + \rho_3}{3} \right]\left[\frac{SNR_1 + SNR_2 + SNR_3}{3} \right] \qquad (5)$$

Running the SFR for 15 steps results in a subset with the best 15 sensors. We repeated this process 100 times for 15 sensors each (over 5,600 regression models were trained). Fig. 1 shows that the optimal subset of the 155 sensors tested has only five members, whereas adding more sensors reduces the performance. Interestingly, a "hybrid" enose with the five best sensors outperforms than any individual instrument.

3.3 Which instrument is best?

To answer this question, we performed SFR on each system individually. Results are summarized in Fig. 2. The best performing systems were from UIUC and UMAN. Note that the performance of the UIUC system is significantly improved (by a factor of 4) by reducing the number of sensors from 108 to 6. In a similar manner, the UMAN unit is also significantly improved (by a factor of 3) by reducing the number of sensors from 8 to 2. In both cases however, a hybrid system of the best five sensors outperforms both by more than a factor of 2.

4. CONCLUSIONS & FUTURE WORK

In this work, we employed four commercial instruments with a history of sensor stability. All four instruments were able to differentiate between cool and hot cars. Separation between leather and cloth interiors was also accomplished for most of the instruments. All the instruments showed some promise for replacing/augmenting the HMG human panel. The best individual sensors for this application are shared between the commercially available iSense and MultiSensor Systems units. More extensive testing is needed to determine if one of these two

machines, acting alone, can achieve acceptable human panel correlation performance goals. The best performance was from a "hybrid" device using sensors from the iSense, NST, and MultiSensor Systems instruments.
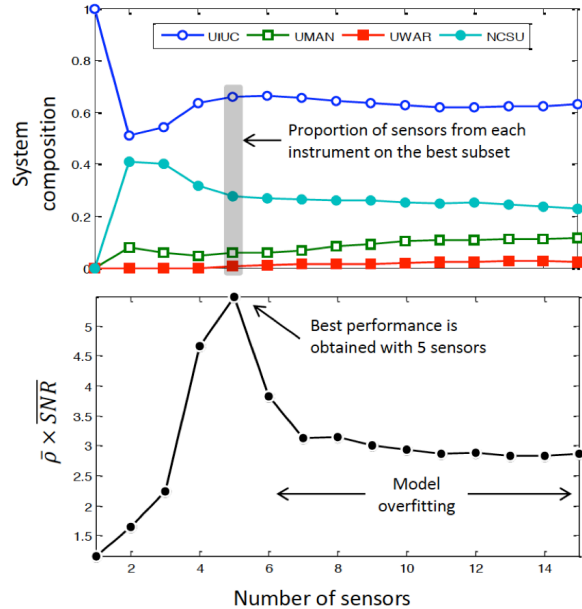

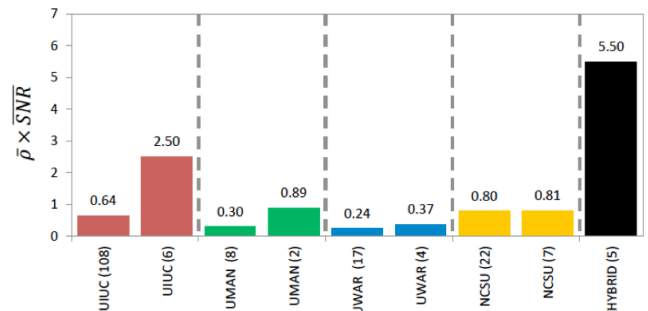**Figure 1.** The best sensors are identified.

Figure 2. The best instrument.

5. REFERENCES

[1] Gutierrez-Osuna R, Schiffman SS, and Nagle HT. Correlation of Sensory Analysis With Electronic Nose Data for Swine Odor Remediation Assessment, Proceedings of the 3rd European Congress on Odours, Metrology and Electronic Noses, Paris, France, June 19-21, 2001.

[2] Verriele M, Plaisance H, Vandenbilcke V, Locoge N, Jaubert JN, and Meunier G, "Odor evaluation and discrimination of car cabin and tts components: application of the "field of odors" approach in a sensory descriptive analysis," *J. Sensory Studies, vol.* 27, pp. 102-110, 2012.

[3] Morvan M, Talou T, and Beziau J-F, "MOS–MOSFET gas sensors array measurements versus sensory and chemical characterisation of VOC's emissions from car seat foams," *Sensors & Actuators B: Chem.,* vol. 95, pp. 212-223, 2003.

[5] Blaschke M, Tille T, Robertson P, Mair S, Weimar U, and Ulmer H, "MEMS gas-sensor array for monitoring the perceived car-cabin air quality," *IEEE Sensors Journal,,* vol. 6, pp. 1298-1308, 2006.

[6] Sakakibara K, Kaitani K, Hamada C, Sato S, and Matsuo M, "Analysis of odor in car cabin," *JSAE Review,* vol. 20, pp. 237-241, 1999.