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# Extraction of spatiotemporal response information from sorption-based cross-reactive sensor arrays for the identification and quantification of analyte mixtures

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## ABSTRACT

Linear sensor arrays made from small molecule/carbon black composite chemiresistors placed in a low headspace volume chamber, with vapor delivered at low flow rates, allowed for the extraction of chemical information that significantly increased the ability of the sensor arrays to identify vapor mixture components and to quantify their concentrations. Each sensor sorbed vapors from the gas stream to various degrees. Similar to gas chromatography, species having high vapor pressures were separated from species having low vapor pressures. Instead of producing typical sensor responses representative of thermodynamic equilibrium between each sensor and an unchanging vapor phase, sensor responses varied depending on the position of the sensor in the chamber and the time from the beginning of the analyte exposure. This spatiotemporal (ST) array response provided information that was a function of time as well as of the position of the sensor in the chamber. The responses to pure analytes and to multi-component analyte mixtures comprised of hexane, decane, ethyl acetate, chlorobenzene, ethanol, and/or butanol, were recorded along each of the sensor arrays. Use of a non-negative least squares (NNLS) method for analysis of the ST data enabled the correct identification and quantification of the composition of 2-, 3-, 4- and 5-component mixtures from arrays using only 4 chemically different sorbent films and sensor training on pure vapors only. In contrast, when traditional time- and position-independent sensor response information was used, significant errors in mixture identification were observed. The ability to correctly identify and quantify constituent components of vapor mixtures through the use of such ST information significantly expands the capabilities of such broadly cross-reactive arrays of sensors.

**Keywords:** electronic nose; sensor arrays; vapor detection; spatiotemporal response; carbon black composite sensors

## 1. INTRODUCTION

Cross-reactive array-based vapor sensors have received significant attention in the recent literature. Such sensors include coated surface acoustic wave devices,<sup>1,2</sup> tin oxide sensors,<sup>3,4</sup> conducting organic polymers,<sup>5,6</sup> polymer-coated micromachined cantilevers,<sup>7,8</sup> dye-impregnated polymers coated onto optical fibers or beads,<sup>9,10</sup> polymer/carbon black composite chemiresistors,<sup>11-16</sup> and low volatility small molecule/carbon black composite chemiresistors.<sup>17</sup> Sensor arrays made from a variety of composite materials encompass a broad range of collective vapor/sensor interactions, producing a diversity of response values upon exposure to a given analyte. Arrays of such sensors, coupled with some form of pattern recognition, are able to discriminate between different vapors.<sup>12, 18, 19</sup> Such arrangements have been termed “artificial” or “electronic” noses, due to their similarities to mammalian olfactory processes.<sup>20,21</sup>

Typical sensor studies to date strive to obtain rapid time-independent responses across all sensors in the array to an unchanging vapor stream. They strive to obtain equilibrium responses between each sensor and the vapor stream being sampled. Under this implementation, reports dealing with cross-reactive sensor arrays have investigated the response and discriminating ability of such arrays toward single analytes.<sup>4, 7, 12, 22</sup> Alternatively, responses to complex mixtures have been used to “fingerprint” complex vapor mixtures rather than identify their constituents. In this approach,

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electronic noses have distinguished between the headspaces generated from different types of beers,<sup>23, 24</sup> hops,<sup>25</sup> wines,<sup>26,</sup>  
<sup>27</sup> vinegars,<sup>28, 29</sup> coffees,<sup>30, 31</sup> and teas.<sup>32, 33</sup>

Rapid time-independent responses used in the above analyses are achieved by using relatively large-volume sensor chambers and exposing the vapor at high flow rates. The large-volume sensor chamber ensures that the vapor being sampled, which partitions into the sensor to trigger a response, does not cause an appreciable decrease in the concentration of material in the sampling stream. The high flow rate ensures that the first and last sensors along the array are exposed to the sampling stream at essentially the same time. Modeling studies utilizing computational fluid dynamics have sought to determine sensor/chamber designs and operational conditions that provide this evenly distributed rapid response.<sup>34, 35</sup>

Exploitation of the spatiotemporal aspects of a non-uniform flow system may, however, yield additional information on the composition of analyte mixtures. The flow dynamics of sniffing, for example, as well as differences in the binding affinities of different odor receptors, are important for odor perception in mammalian olfaction. In humans, at any time, the vapor flow rate is different through the two nostrils of a given individual. This is caused by blood flow-induced occlusions in the nostrils, which varies with time, thus causing an individual's high- and low-flow nostril to vary with time. These varying flow patterns have been shown to affect odor perception.<sup>36</sup> Consistently, a sensor chamber modeled after a canine nasal cavity, having sensors placed throughout the cavity, has been shown to provide enhanced discrimination in various classification tasks relative to a single sensor array placed solely at the inlet of the cavity.<sup>37</sup>

Recently, arrays of polymer/carbon black composite sensors have been placed in a chamber with a low headspace volume while analyte vapor was sampled at various flow rates. Depending on the vapor flow rate, pure test vapors and test vapor mixtures showed a concentration profile along the array as a function of time.<sup>38</sup> In this approach, the sensor material acted similarly to a stationary phase in a gas chromatography column, with vapors partitioning into the sensor material as dictated by their solid/gas partition coefficient,  $K_{eq}$ . The vapor species are not physically changed; the vapors are simply sorbed and retained by the sensor material. The progress of each vapor front down the sensor array is dictated by the flow rate, chamber geometry, and mass uptake by the upstream sensor films.

In this work, arrays of low volatility organic molecule/carbon black composite vapor sensors have been exposed to various vapor mixtures in a low headspace volume chamber. In this configuration, the sensor material acts to separate the analyte to produce a space- and time-dependent signal response from the sensors in the array. A collection of such sensor arrays were first exposed to, and trained against, pure vapor species, each exposed at 5% of their saturated vapor pressure,  $P/P^o = 0.050$ , where  $P$  is the partial pressure and  $P^o$  is the saturated vapor pressure of the analyte of interest. The sensor arrays were then challenged by exposures to various mixtures of these test vapors. A linear, statistically based chemometric method, non-negative least squares (NNLS), was used to evaluate the data. In each case, no *a priori* information was used regarding which vapors in the training set were present in the challenge mixtures. The performance of the spatiotemporal (ST) array arrangement in the identification of mixtures was then compared to the performance of an array having an equal number of sensor response descriptors using a traditional sensing approach. In the traditional approach all sensors were exposed to identical, time-independent streams of analyte vapor.

## 2. EXPERIMENTAL

### 2.1 Materials

The insulating materials for fabrication of the sensor films consisted of tetracosane (99%), lauric acid (99.5%), and dioctyl phthalate (99%), purchased from Aldrich; as well as propyl gallate (98%) and quinacrine dihydrochloride dihydrate (97%), purchased from Acros Organics. Reagent grade toluene, tetrahydrofuran (THF), and chloroform, received from Aldrich, were used as solvents in the sensor suspensions. Hexane (95%), decane (99%), ethanol (95%), *n*-butanol (99.9%), ethyl acetate (99.5%) and chlorobenzene (99%), purchased from Aldrich, were used to generate vapors for delivery to the sensor arrays. Black Pearls 2000 (BP 2000), a furnace carbon black (CB) material donated by Cabot Co. (Billerica, MA), was used as the conductive phase in the sensor composites. All materials were used as received.

## 2.2 Detectors

Four suspensions, each comprised of a non-conductive sorption phase and a conductive carbon-black (CB) phase, were used to fabricate the sensors evaluated in this work, listed in Table 1. First, the non-conductive (non CB) sensor material(s) were placed in  $\approx 60$  mL of solvent and the solution was sonicated for  $>10$  min. CB was added to the solution, and the resulting mixture was sonicated for  $>30$  min to produce a well-dispersed suspension. Dioctyl phthalate (DP) was used as a component of some of the sensor films, to serve as a plasticizer. The plasticizer adds to the sensor array diversity, as well as increases the analyte permeability, generating the more rapid sensor responses needed for the ST response analysis.<sup>13, 16</sup>

Table 1. Suspensions used to make sensors. Non-conductive materials were sonicated in 60 mL of solvent for  $>10$  minutes. CB was then added and the solvent again sonicated for  $>30$  minutes to generate well-dispersed suspensions.

suspension	sensor materials	solvent
1.	35 mg tetracosane, 15 mg DP, 150 mg CB	toluene
2.	35 mg lauric acid, 15 mg DP, 150 mg CB	tetrahydrofuran
3.	50 mg propyl gallate, 150 mg CB	tetrahydrofuran
4.	50 mg quinacrine dihydrochloride, 150 mg CB	chloroform

Detector array substrates were fabricated by evaporating 30 nm of Cr and then 70 nm of Au onto standard 75 mm x 25 mm glass microscope slides. A custom-made mask was used to produce the electrode pattern shown in Figure 1.<sup>38</sup> The slide was masked with Teflon tape and sprayed with a single sensor suspension using an airbrush (Iwata, Inc.).<sup>12, 17, 38</sup> Several pairs of electrodes were monitored with an ohmmeter, and spraying was continued until the resistance across the 0.4 mm sensor electrode gaps was 500 - 1500  $\Omega$ . This created an overall sensor film of 75 x 5 mm in length and width, having a film thickness of  $\approx 1$ -3  $\mu\text{m}$  as measured with a Dektak 3030 profilometer (Sloan Technology Corp., Santa Barbara, CA). Four such detector substrates were made using the suspensions listed in Table 1.

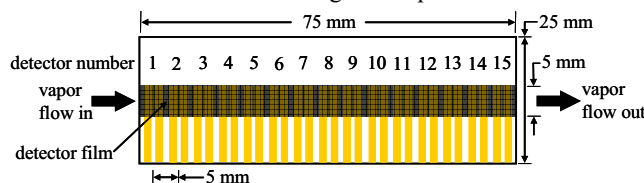


Figure 1. Sensor substrate schematic. Sensor solutions from Table 1 were sprayed with an airbrush to generate detector films. 15 pairs of gold electrodes deposited along the length of the substrate allowed for the monitoring of 15 sensors.

The four arrays were then placed into the custom-made aluminum sensor chamber depicted in Figure 2. The chamber was 110 mm long and 25 mm wide. In this study, only one side of the glass slide was coated with sensor material, so a total of 60 sensors were available for monitoring. A symmetric Teflon gasket was used to divide the incoming flow evenly among each of the eight vapor flow pathways. Additionally, for each of the vapor flow pathways, the inside of the aluminum chamber was covered with a film of Teflon tape. Two weeks passed between the spraying of the sensor films and the initiation of the train/test phase.

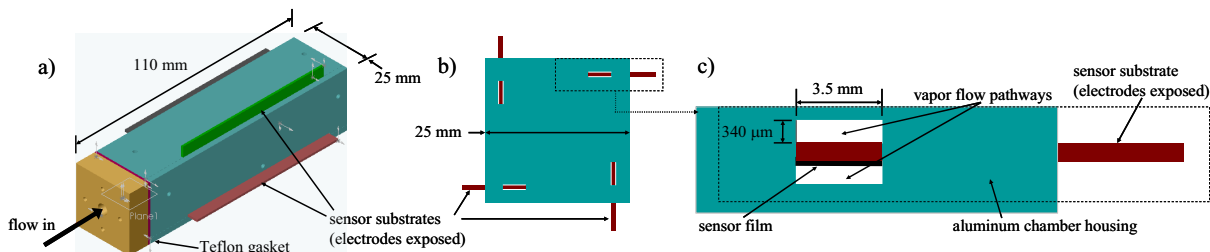


Figure 2. Sensor chamber schematic. a) 3-dimensional view of the assembled chamber. Three of the four inserted substrates are shown. b) Sensor chamber, shown head-on with the end cap and Teflon gasket removed, with the four inserted substrates and eight vapor flow pathways. c) Not-to-scale close-up of a single substrate from (b).

### 2.3 Vapor generation and delivery

A previously described automated flow system, controlled by LabVIEW 5.0 software, was used to deliver pulses of diluted streams of solvent vapor to the detectors.<sup>12, 14, 17, 38</sup> Pure analyte vapors were presented to the sensor arrays at  $P/P^o = 0.010, 0.030, \text{ and } 0.050$  (1, 3, and 5 parts of foreground saturated vapor flow combined with 99, 97, and 95 parts of background air, respectively). Eight exposures were performed at each analyte concentration, for a total of 24 exposures per vapor. These pure analyte exposures were randomly delivered over all analytes and concentrations. Only exposures where  $P/P^o = 0.050$  were used as the “training” exposures. Exposures for the training period occurred over a 16-hour period.

Analyte vapor mixtures were generated by mixing equal volumes of each component. Background air bubbled through these mixtures was presented to the sensor arrays at  $P_{mix}/P^o_{mix} = 0.050$ , where  $P_{mix}$  is the sum of the partial pressure of the analytes and  $P^o_{mix}$  is the vapor pressure of the mixture. Twenty exposures of each of the mixtures were presented to the sensor arrays. These mixture exposures served as the “testing” exposures. Three exposure periods occurred over 13 h each, randomly exposing 2- and 3-component mixtures, 3- and 4- component mixtures, and 4- and 5- component mixtures. All training and testing data were collected during a five day period.

A total flow rate of  $150 \pm 5 \text{ mL min}^{-1}$  ( $19 \text{ mL min}^{-1}$  per chamber vapor flow pathway) was provided to the sensor chamber during the flow of either background or analyte vapor. To achieve flows with minimal variance in the rates of both the background and foreground streams, the mixtures were first generated at higher flow rates of  $400 \text{ mL min}^{-1}$ . A small Teflon-lined sampling pump (Science Pump Corporation) was used to withdraw vapor from the  $400 \text{ mL min}^{-1}$  stream. Withdrawn flow was vented directly to the hood, and non-withdrawn flow was presented to the sensor chamber at  $150 \pm 5 \text{ mL min}^{-1}$ . Flow meters (Gilmont) were used to monitor the flow rates of the background and undiluted vapor streams, as well as to monitor the flow rate immediately prior to the entrance to the sensor chamber.

Gas chromatography-mass spectrometry (GC-MS) (Hewlett Packard 6890 GC system; Hewlett Packard 5973 Mass Selective Detector) was used to independently validate the compositions of the vapor mixtures. For each of the pure test analytes, the vapor stream delivered at a setting of  $P/P^o = 0.050$  to the sensor chamber was sampled and manually injected into the GC. The GC-MS spectral peaks were then integrated to provide a calibration for that analyte at the generated fractional vapor pressure of  $P/P^o = 0.05$ . Streams of the various mixtures were then sampled and injected into the GC, and the GC-MS spectral peaks of each individually eluted analyte were integrated. The fractional vapor

pressure of each species  $i$  in the mixture was calculated as  $\left(\frac{P}{P^o}\right)_i = \frac{A_i}{A_i^{cal}} \times 0.050$ , where  $A_i$  is the integrated area of species  $i$  in the mixture, and  $A_i^{cal}$  is the integrated area of species  $i$  in the calibration performed at  $P/P^o = 0.050$ . For all mixtures, a standard error propagation was performed. For the calibration of pure analyte vapors, at least six measurements were taken, while for mixtures, at least three measurements were taken. Mixtures consisting of 2, 3, 4, and 5 components were generated from the six test analyte vapors.

### 2.4 Measurements and data pre-processing

Sensor film resistances were measured using a Keithley 2002 multimeter and a Keithley 7001 multiplexer. Each sensor substrate was connected to the multiplexer through shielded, twisted pair cables and a rotary ZIF connector (Tyco Electronics). To increase the overall sampling frequency, two Keithley 2002/7001 combinations were used to record the sensor response data. Each Keithley 2002/7001 combination recorded the responses from two of the four arrays, or 30 of the 60 total sensors. Sensor films were intentionally sprayed to produce film resistances within the resistance range,  $1000 \pm 500 \Omega$ , to increase multiplexing speed. Each sensor was sampled approximately every 3 s. Train and test exposures consisted of 70 s of pure background flow over the sensor arrays to establish a baseline resistance, followed by 150 s of analyte vapor flow at the desired fractional vapor pressure ( $P/P^o = 0.010, 0.030, \text{ or } 0.050$ ), followed by a stream of pure background flow for 230 s to restore the sensors to their initial states. Prior to data collection, the sensors were subjected to 24 h of randomized exposures to all of the test vapors. Pure vapors were first used to train the sensor arrays, followed by testing of the array with exposures to mixtures. All sets of exposures were randomized.

The response of each vapor detector for each analyte exposure was expressed as  $S(t) = \Delta R(t)/R_b(t)$ , where  $R_b(t)$  is the baseline-corrected resistance of the detector in the absence of analyte and  $\Delta R(t)$  is the time-varying, baseline-corrected, resistance change upon exposure to the analyte.<sup>14, 17</sup> The baseline resistance,  $R_b(t)$ , was obtained by fitting a straight line to the data obtained during the pre-exposure period. If the range of possible line slopes included zero at a 95% confidence level, it was determined that any sensor drift was insignificant and responses were used as recorded. If the range of line slopes did not include zero at the 95% confidence level, it was determined that the drift was significant, and the slope was used to extrapolate the resistance recorded immediately prior to exposure to the resistance at any time  $t$ . Figure 3 gives an example of this baseline correction process for a propyl gallate/CB sensor (suspension 3, Table 1) exposed to hexane at  $P/P^o = 0.05$ .  $\Delta R(t)$  was calculated by subtracting  $R_b(t)$  from the measured sensor resistance at time  $t$ . The actual times at which the sensor resistances were recorded varied with each exposure, and were different for each sensor in the array. The responses at the times used in the data analysis were calculated by interpolating between the measured data points.

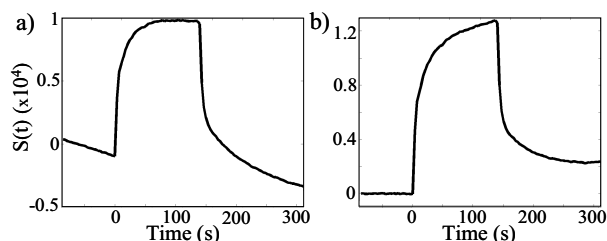


Figure 3. Baseline drift correction for sensor 15 along a propyl gallate/CB sensor array (suspension 3, Table 1) responding to hexane at  $P/P^o = 0.05$ . a) uncorrected; b) corrected.

In a control study, only the first, middle, and last sensor in each array (i.e., detectors 1, 8 and 15 in Figure 1) were sampled. This data set also captured ST sensor response information, albeit with fewer data points. These data were then compared to “traditional” data obtained from the responses of the first three sensors in each array. The traditional data were acquired when all sensors were in equilibrium with the initial vapor stream, near the end of the 150 s vapor exposure period. To facilitate comparisons between the two methods, the same total number of  $S(t)$  values were extracted in both cases. This procedure produced an equal number of total response descriptors from the three-sensor subarrays used to compare the ST and traditional sensing approaches.

## 2.5 Vapor classification

The responses of these chemiresistive composite vapor sensors have been shown to be linear with the concentration of analyte over the range of concentrations of interest in this work.<sup>14, 17</sup> A statistical, linear-based pattern recognition technique was therefore used to determine the identity and relative amounts of each analyte present in the vapor mixtures. Non-linear, neural network-based pattern recognition implementations may potentially provide enhanced performance in such tasks, but linear-based algorithms provide a more objective measure of performance. Hence, non-negative least squares (NNLS) was used to analyze the ST array responses of analyte mixtures.<sup>39</sup>

Training data collected at  $P/P^o = 0.050$  were used to generate a vapor response library. Averaged baseline-corrected responses to the six vapors,  $S(t)$ , extracted at four times ( $t = 5, 15, 55$  and  $75$  s) for each of the fifteen sensors along each of the four arrays, were used to create a  $240 \times 6$  library,  $\mathbf{A}$ , of responses to the six pure analyte vapors. NNLS minimizes  $\|\mathbf{Ax}-\mathbf{b}\|$ , where  $\mathbf{b}$  is the  $240 \times 1$  measured sensor response vector to the mixture, and  $\mathbf{x}$  is a  $6 \times 1$  vector of concentrations of the analytes that minimizes the objective function, subject to  $x_i \geq 0$ .<sup>39</sup> All data analysis was performed in MATLAB.

## 3. RESULTS

### 3.1 Sensor response

Figure 4a-b shows the baseline-corrected response of one 15 element sensor array (lauric acid/CB; sensor 2, Table 1) to (a) pure butanol and (b) pure decane each presented at  $P/P^o = 0.050$ , as a function of time. Responses were time-shifted so that analyte was physically delivered to the sensors at  $t \approx 0$  s. The experimental setup, consisting of several feet of 1/16” Teflon tubing as well as a flow meter situated immediately prior to chamber entrance, produced a delay of  $\approx 8$  s

between the initiation of analyte delivery and the response of the first sensor in the array; thus, analyte delivery was initiated at  $t \approx -8$  s, while analyte arrived at the sensor arrays at  $t \approx 0$  s. For visualization, the responses have been normalized by the response of each of the sensors at  $t = 140$  s. Responses were observed on two times scales: an immediate rapid response, and a slower drifting response. The latter can be attributed to vapor front broadening due to Taylor dispersion occurring in the Teflon tubing and flow meter prior to the chamber.

On exposure to butanol ( $P^o = 6$  mm Hg),<sup>40</sup> the vapor concentration became uniform over all sensors in the array within approximately a 10 s window. In contrast, on exposure to decane ( $P^o = 1$  mm Hg),<sup>40</sup> the response across the array varied significantly. The first sensor exhibited a fairly rapid response. However, subsequent sensors exhibited significantly time-delayed responses due to the high degree of mass uptake. The sorption of decane vapor by the earlier sensors therefore altered, and delayed, the concentration of analyte in the vapor front to the subsequent sensors along the array. The sensor material acted as a GC stationary phase, taking up and establishing equilibrium with the components of the vapor-phase flow stream. Partition coefficients are inversely proportional to vapor pressure,<sup>41</sup> which explains the different degrees of mass uptake for the two situations.

Figure 4c shows the baseline-corrected response of the sensor array exposed to a mixture of butanol and decane delivered at  $P_{mix}/P^o_{mix} = 0.050$ . The first sensor in the array was exposed to a vapor stream that contained a mixture of butanol and decane at their original concentrations. This sensor exhibited a response that rapidly became nearly independent of time. In contrast, latter sensors along the array exhibited a two-step response. The first step captured the fairly rapid progression of butanol along the array, shown in Figure 4a. The second step exhibited a time-dependent delayed response that captured the progression of decane along the array, as seen in Figure 4b. The 1<sup>st</sup> rapid portion of the sensor response shown in Figure 4c is indicative of butanol progressing along the array. The 2<sup>nd</sup> time-dependent portion of the response shown in Figure 4c is indicative of decane progressing along the array.

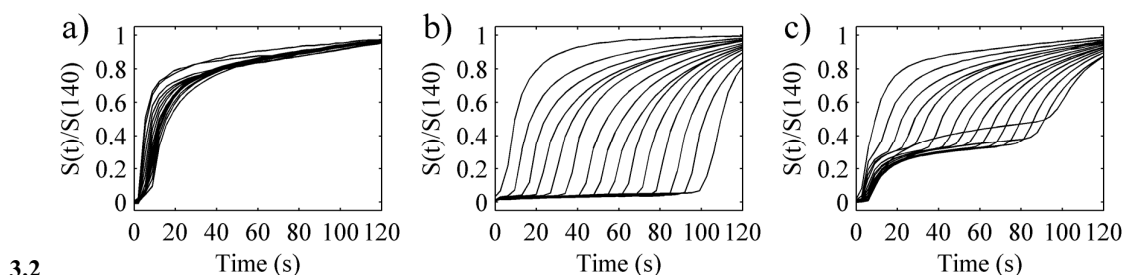


Figure 4. 15-sensor array response of sensor 2 (Table 1) exposed to a) butanol delivered at  $P/P^o = 0.05$ ; b) decane delivered at  $P/P^o = 0.05$ ; and c) a mixture of butanol and decane delivered at  $P_{mix}/P^o_{mix} = 0.050$ . Individual sensors are normalized by their respective response at  $t=140$  s to place all responses on the same scale.

### 3.3 Analysis of mixtures

All mixtures were analyzed using GC-MS to obtain a baseline measurement for the quantity of each component present in each mixture, in terms of fractional vapor pressure. Table 2 displays these concentrations for each of the 14 mixtures as  $1000 \times P/P^o$ . Mixtures were also analyzed using the ST response data produced on the sensor array. For all exposures, the observed  $S(t)$  values were interpolated to fixed times having 10 s intervals, to produce 15 array responses for each array element in the time interval of  $t = 5$  to 145 s. Subsets of these data, comprised of  $S(t)$  responses extracted at various times, ranging from single time-response descriptions to multiple time-response descriptions (including up to 7 different times), were then subjected to analysis using NNLS.

The sum of the squared residual variance,  $\chi^2$ , was calculated between the mean mixture composition calculated by NNLS and the mixture composition indicated by GC-MS measurements, shown in Table 2. The optimal time combination was chosen as the combination of times that provided the lowest  $\chi^2$  (best fit) between the deduced sensor array mixture composition and the mixture composition indicated by GC-MS. The optimal time combination was four times, at  $t = 5, 15, 55$  and  $75$  s. The  $S(t)$  values extracted at  $t = 5$  and  $15$  s (i.e., immediately after vapor delivery) provided information about the movement of higher-vapor pressure (lower-partitioning) analytes such as hexane, ethyl acetate and ethanol ( $P^o = 130, 80$  and  $50$  mm Hg, respectively)<sup>40</sup> along each array. The  $S(t)$  values at  $t = 55$  and  $75$  s

provided information on the progress of lower-vapor pressure (higher-partitioning) analytes, such as chlorobenzene, butanol and decane ( $P^o = 10, 6$  and  $1$  mm Hg, respectively)<sup>40</sup> along each array. Although this combination of analysis times provided the lowest  $\chi^2$  between the sensor array and the GC-MS results, many combinations using 2-7 times (instead of 4), spanning approximately the same range of overall analysis times, provided comparable overall performance to that of the optimal 4-time data set.

Table 2. Fractional vapor pressures ( $\times 1000$ ) of analyte vapors present in each of the mixtures, determined by GC-MS sampling immediately prior to chamber delivery.

mixture	hexane	decane	ethyl acetate	chloro-benzene	ethanol	butanol
1	0	23±11	27±15	0	0	0
2	0	0	13±2	24±1	0	0
3	0	0	0	23±1	0	22±1
4	0	20±1	0	0	0	31±2
5	0	11±3	8±7	20±4	0	0
6	23±2	0	0	0	29±8	44±16
7	27±8	14±8	0	0	0	44±13
8	0	0	4±1	12±1	23±6	0
9	22±7	0	0	28±11	45±9	0
10	18±4	12±4	0	0	27±4	11±3
11	9±8	14±2	0	22±6	0	69±27
12	13±8	11±4	8±2	0	31±6	20±5
13	12±0	0	4±0	8±1	23±2	13±2
14	8±0	5±0	4±0	8±0	27±2	0

For exposure of the sensor arrays to 2-, 3-, 4-, and 5-component mixtures, Figures 5a-d, respectively, show the identified analytes and their estimated concentrations (●) in the analyte mixtures, as obtained from analysis of the ST response data using NNLS and various sensor combinations. These figures also display the concentrations of analytes as revealed by GC-MS analysis (□). Figures 5a-d.i display these analyses using responses from all 15 sensors in each array, with responses at  $t = 5, 15, 55$  and  $75$  s, and NNLS to identify the vapor constituents and reveal their respective concentrations.

Analyses were also performed using the responses produced by a limited number of sensors along each array. In this approach, the responses from the first, middle and last sensor along each array (detector positions 1, 8 and 15 in Figure 1) were sampled at  $t = 5, 15, 55$  and  $75$  s, thus providing a data set that contained ST information from only three sensors per array. The twelve sensors that were not sampled provided a GC stationary phase equivalent that acted to separate vapors as they progressed down the length of each array. Figures 5a-d.ii display analyses for 2-5 component mixtures using the first, middle, and last sensor along each array and NNLS. Generally, using all 15 sensors along each array, or using only the first middle and last sensor along each array, yielded identical mixture analysis.

To compare the results obtained using the ST approach with results obtained using the traditional sensing approach, data were obtained using sensor responses produced by exposure to an unchanging analyte stream. This was achieved by using the first three sensors in each array sampled at  $t = 135, 140, 145$  and  $150$  s. Of the vapors present in the sampled mixtures, decane possessed the lowest vapor pressure. The degree of analyte partitioning, dictated by the partition coefficient, is inversely proportional to the vapor pressure of the analyte, thus decane progressed most slowly down each sensor array. Figure 4b shows the response of a sensor array upon exposure to decane, indicating that the first three sensors showed a fairly rapid response, and by 135 s essentially came to an equilibrium response to the sampled vapor stream (note: figure only goes up to  $t = 120$  s). Responses were calculated at four separate times, to provide the ST and non-ST method with an equal number of total response descriptors.

Figures 5a-d.iii display the results obtained using non-ST “traditional” detection with the first three sensors per array on exposure to 2-, 3-, 4-, and 5- component mixtures, respectively. Comparing these results with those presented in Figures 5a-d.ii indicates that the traditional sensing approach produced a marked decrease in the ability of the sensor arrays to



correctly identify and quantify the presence of vapors in the tested mixtures. An equal number of response descriptors were used for this ST/traditional mixture analysis comparison.

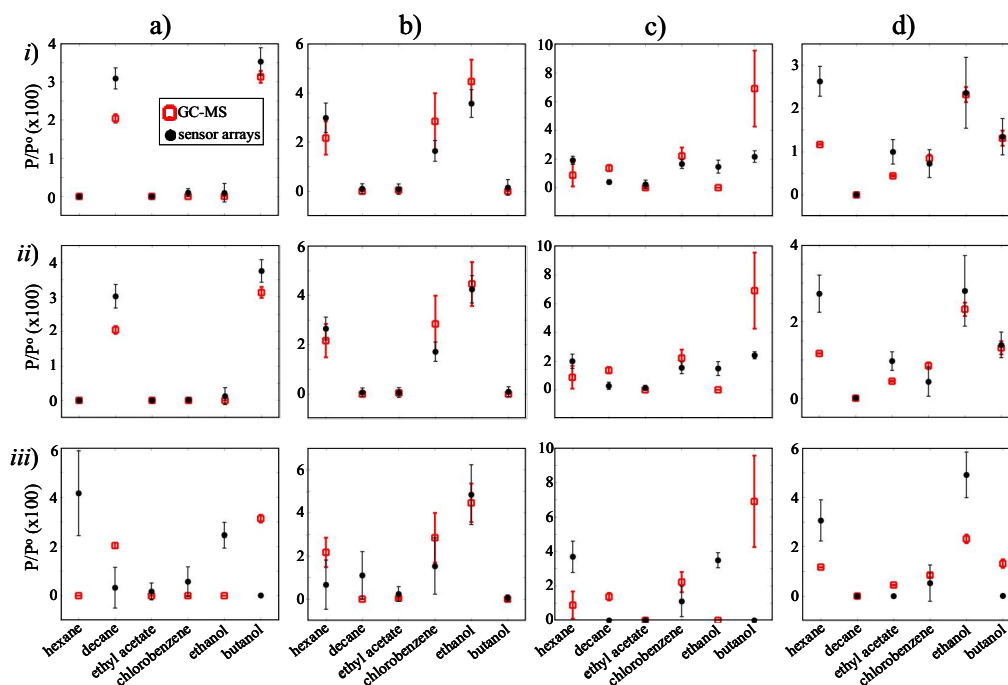


Figure 5. Comparison between GC-MS mixture analysis and sensor array mixture analysis using NNLS and various sensor configurations. Columns: a) 2-component mixture; b) 3-component mixture; c) 4-component mixture; d) 5-component mixture. Rows: *i*) ST analysis using sensors 1-15 along each array; *ii*) ST analysis using only sensors 1, 8, and 15 along each array; *iii*) non-ST analysis using only sensors 1-3 along each array and  $S(t)$  calculated at  $t = 135, 140, 145$  and  $150$  s for each sensor (vs.  $t = 5, 15, 55$  and  $75$  for ST analysis).

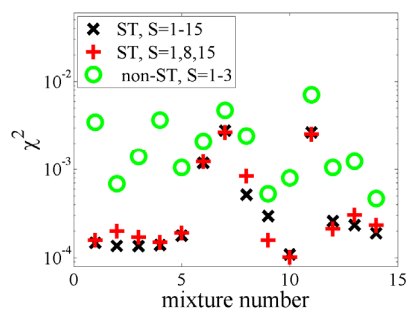


Fig. 6. Residual squared error ( $\chi^2$ ) between mixture identification as calculated with GC-MS, and mixture identification as calculated using NNLS and various sensor arrangements: ST analysis using all 15 sensors along each array, ST analysis using the first middle and last sensor along each array, and non-ST analysis using only the first three sensors along each array.

Figure 6 displays the sum of the residual squared error for each of the fourteen mixtures analyzed in this work. The results are presented for data analyzed using NNLS with 1) ST detection with the full 15 sensors per array; 2) ST detection with only the first middle and last sensors (sensors 1, 8, and 15) along each array; and 3) the traditional non-ST approach with only the first three sensors along each array. Vapor detection using ST response data, whether employed with the full 15 sensors per array or the limited 3 sensors per array, yielded approximately equal errors for each of the mixtures. In contrast, the largest errors for each of the analyzed mixtures were obtained using the non-ST response information provided by the first three sensors in each array. For every situation investigated, the use of the ST aspects

of the array response produced significantly better performance in the identification and quantification of the components of the vapor mixtures than the results obtained using the traditional detection approach.

#### 4. DISCUSSION

Sorption-based sensors such as those used herein have been shown to exhibit a linear response with respect to pure analyte vapors at relatively low concentrations (i.e.,  $P/P^o < 0.05$ ), as well as a linear response with respect to multiple vapors.<sup>14, 17</sup> The development of the ST approach described herein is predicated on this response linearity. The sensor response is essentially a dual-step process. First, chemical thermodynamics cause a given vapor to partition into the sensor film, which causes it to volumetrically expand. This expansion causes a change in the conductive properties of the film, which is linear when operating beyond the percolation regime of the composite film and over small volumetric changes.<sup>15, 42</sup> The simplest model for the sorption behavior is given by the Langmuir adsorption isotherm, which predicts linear sorption at low concentrations over all species adsorbed.<sup>43, 44</sup> This model assumes no interaction between any sorbed species, and assumes that all sorption sites are energetically uniform. At high concentrations, or in situations where interactions exist between adsorbed species, this linearity breaks down.<sup>43, 44</sup> While Figure 5 displays an unprecedented ability to identify mixtures, deviations are evident between actual mixtures presented and sensor array perception. These deviations are likely due to a change in adsorption energies when vapors are present at high concentrations, or in unfavorable combinations, in the sensor film. These energy differences will vary to different degrees depending on the species adsorbed, causing the sensor to wrongly identify a given mixture.

The use of ST response data for vapor detection allowed for the extraction of important sensor/vapor response information not available using the traditional sensing approach. In this work, unnormalized baseline-corrected response data were used, to preserve information regarding the concentrations of the vapors in the test analytes. However, often

sensor data is normalized by  $\overline{S_i(t)} = \frac{S_i(t)}{\sum_{i=1}^{ns} \sum_{t=1}^{nt} S_i(t)}$  where  $S_i(t)$  is the response extracted from sensor  $i$  at time  $t$ ,  $ns$  is the

number of sensors used, and  $nt$  is the number of times used to extract a response  $S_i(t)$ .<sup>12, 17</sup> This normalization procedure creates a unit vector response for each exposure, largely independent of concentration, that can be used as a fingerprint for an individual analyte. Performing principal components analysis (PCA) on normalized response data often reveals that the vast majority of the array response variance is contained in only a few principal component (PC) vectors.<sup>17, 45</sup>

Performing PCA on normalized ST pure vapor training data of the 15 sensors per array indicated that PCs 1-5 contained 35, 22, 15, 9 and 4% of the total array variance, respectively. Performing the same PCA using the normalized 3 sensors per array ST vapor training data similarly revealed that PCs 1-5 contained 37, 21, 14, 8 and 6 % of the total array variance, respectively. The similarities in the PC eigenvalues for the two cases suggest that no significant additional information was extracted by using the data from the full 15 sensors in the array.

These findings are reflected in Figures 5a-d.i and 5a-d.ii, which show approximately equal performance for mixture identification for the two approaches. When PCA was performed on pure vapor training exposures for the normalized traditional data set using the first three sensors in each array, the PCs 1-5 contained 65, 20, 9, 2 and 2% of the total array variance, respectively. While 85% of the variance is contained in only the first 2 PCs, 5 PCs were required for the ST data. For both approaches, the data sets used an equal number of response descriptors. The differences in eigenvalue decomposition and in mixture analysis performance reflect the limited amount of information obtained using the traditional sensing approach relative to the ST approach, shown in Figure 5a-d.iii. Spreading out the variance over more PCs translates into more unique information, and an increased ability to analyze vapor mixtures, in accord with the results and conclusions reported herein.

A single flow rate was employed in this study. The six pure analyte vapors chosen represented various chemistries and additionally spanned two orders of magnitude in vapor pressure. Hence, the given sensor arrangement and implementation proved sufficient to identify and quantify mixtures of the chosen vapors. However, as shown in Figure 4b, for some analytes the latter sensors may never reach equilibrium with the concentration of the initially sampled vapor stream. Thus, additional response information, including finer resolution of the progression of the analyte vapor down each array, could be extracted by using longer exposures, longer length arrays or through the use of multiple vapor flow rates. One limit of implementation of this approach would involve the use of an infinitely slow flow rate slow, limited

by the rate of diffusion of vapors down the array. Under these conditions, the desired mass depletion effects would be maximized. However, vapor front broadening would become significant because diffusion would be the dominant mode of mass transport along each array. This vapor front broadening would cause the sharp differences in sensor response observed in Figure 4b to diminish, with the relevant ST response information being overshadowed by sensor noise. The other limit of ST implementation would be the use of an infinitely long sensor array, which would be the equivalent of a GC column with sensors located along its length. An infinitely long sensor array would also cause significant vapor front broadening and a loss of ST information, due to significant Taylor dispersion that would occur along the long flow pathway. Modeling work is currently underway to search for and define an optimal operational regime that maximizes the amount of ST information extractable from such sensor arrays.<sup>46</sup> This optimal regime will be defined by the ratio of several chamber geometries and vapor delivery flowrates, and will take into account vapor front broadening as well as the ability of a given chamber geometry to allow for the desired mass depletion effects observed here.

An improved geometric implementation maximizing the information extracted per sensor employed would involve exponentially spaced sensors. Such spacing would more efficiently capture the ST response differences for analyte vapors having a large range of partition coefficients with the sensor films. Because approximately the same results were obtained when the ST responses were described by 3 or 15 sensors per array, only a limited number of sensor response descriptors were required for the vapors evaluated. The limited case of 3 sensors using ST information sufficiently captured the necessary information to perform mixture analysis with the sensor arrays. In this case, the chosen vapors possessed sufficient differences in chemistries and vapor pressures, and only a fraction of the total sensors were required. Alternatively, had the vapors been more similar chemically, greater detail may have been required for mixture identification, and differences between the analysis of the ST response set containing the full 15 sensors per array and the limited set containing only 3 sensors per array would be observed. An exponential distribution of sensors along each array would maximize the information extracted per sensor, and decrease the cycling time required between the measurements of each sensor.

In this work, the sensor material was a sorption-based composite comprised of small organic molecules and carbon black. Such films not only performed the vapor sensing function, but also served as the stationary phase into which the vapors partitioned and separated. The chemiresistive sensor films can be deposited and remain functional in most any form factor, making them especially attractive for use in the ST array response implementation. Many sorption-based sensors, however, are restricted in terms of the forms in which they can be fabricated: coated quartz crystal microbalances, for instance, are restricted to the shape of the underlying quartz substrate. In situations such as these, in which one can not assemble the sensors in the type of array used here, ST mixture analysis could be applied by maintaining a low vapor headspace volume, and coating the walls of the chamber with various sensing (e.g., carbon black composites) or non-sensing (e.g., traditional chromatographic) stationary phases. For these cases, the only restriction would be that the sensors themselves must be linear with concentration and additive with respect to multiple vapor responses. If these criteria are met, the ST approach could be used with a wide variety of sensor types.

The ST data reported herein were obtained in a controlled laboratory setting. The flowrate to the sensor chamber was set at 150 mL min<sup>-1</sup>, and ranged from 145 to 155 mL min<sup>-1</sup> with random fluctuations throughout the training and testing periods. These fluctuations were accounted for during the training phase of the sensors. Had higher flowrate precision been achieved, the sensors would exhibit less variance in their responses, providing enhanced ability to correctly identify mixtures. Additionally, if the flowrate exhibited a systematic drift, the fingerprint response of each of the vapors could change significantly, causing degradation in the ability to correctly identify mixtures. To better understand how well this ST approach would perform in the real world, further work should be done to investigate how sensitive and/or robust this approach is to changes in exposure flowrate, as well as fluctuations/changes in temperature, humidity, and sensor response drift. Furthermore, previous work has shown the ST method can readily detect low concentrations (ppb) of low vapor pressure analytes in the presence of higher concentrations (ppm) of high vapor pressure analytes.<sup>38</sup> Additional studies should be performed to better understand to what extent the ST method is able to identify a vapor present at low concentration in the presence of vapor(s) present at higher concentrations.

## 5. CONCLUSIONS

Use of ST data has been shown to provide enhanced performance in analysis of vapor mixtures relative to the traditional steady-state response of an array of broadly cross-reactive vapor sensors. In a low-volume headspace chamber that allows each sensor to be exposed to a well-defined, time-varying vapor stream, the sensor material acts as a

chromatographic stationary phase, causing vapors to be retarded in progression along the array. The retardation is proportional to the sensor/vapor partition coefficient. The resulting sensor responses at long times and/or at positions close to the inlet captures the traditional sensor response differences to an unchanging vapor stream, but at shorter times and positions further from the inlet, also measures the progress of each vapor down the sensor array. Under such conditions, significantly more information is obtained on analyte mixtures relative to the information obtained using traditional sensor responses alone. Modeling of the ST approach to define an optimal operational regime that maximizes the amount of extracted ST information is currently underway.

Previous reports using cross-reactive sensor arrays have addressed pure vapor identification, or the identification of complex mixtures as a whole, but the identification and analysis of mixtures containing more than three components has not been previously achieved. The ability of an ST sensor array consisting of only four sensor types to correctly identify and quantify 2-, 3-, 4- and 5-component mixtures, using a library consisting of responses to six pure analyte vapors, demonstrates the importance of the use of ST information. The implementation of the ST method thus clearly increases the possible application space of such sensor arrays for analysis of analyte mixtures, as well as for analysis of pure analytes.

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