

Supramolecular Chemistry Approach to the Design of a High-Resolution Sensor Array for Multianion Detection in Water

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Abstract: Reliable sensing of structurally similar anions in water is a difficult problem, and analytical tests and sensor devices for reliable sensing of multiple anions are very rare. This study describes a method for fabrication of simple colorimetric array-based assays for aqueous anion solutions, including complex analytes encountered in real-life applications. On the fundamental level, this method shows how the discriminatory capacity of sensor arrays utilizing pattern recognition operating in multianalyte environments may be dramatically improved by employing two key features. The synergy between the sensor and hydrogel host resembles the cooperative effects of an apoenzyme and cofactor: the host hydrogel helps extract the target anions from the bulk analyte while stripping the solvate molecules off the anions. In addition, the supramolecular studies of the affinity and selectivity of the potential sensors for target analytes allow for constructing an array predesigned for a particular analyte. To illustrate both aspects, an eight-sensor array utilizing colorimetric sensor materials showing selectivity for fluoride and pyrophosphate while displaying significant cross-reactivity for other anions such as carboxylates, phosphate, or chloride was used to differentiate between 10 anions. The quantitative analyses were also performed to show that the eight-sensor array was found to operate across 4 orders of magnitude concentrations (0.20–360 ppm; 10 μ M to 20 mM). The applicability of this approach was demonstrated by analyzing several toothpaste brands. The toothpastes are complex analytes comprising both known and unknown anions in various concentrations. The fluoride-selective yet cross-reactive array is shown to utilize the fluoride content as the main differentiating factor while using the remaining anionic components for further differentiation between toothpaste brands.

Introduction

Increased understanding of the environment, industrial and biological processes, and medical conditions presents us with complex analytical problems requiring development of accurate chemosensors,^{1–3} as well as methods of evaluating the data outputs.⁴ One of the most intriguing problems in the chemosensor field is multianalyte sensing.^{5–7} In general, sensing in multianalyte environments may be achieved by multiple target-selective sensors, each one with high affinity for one specific target. Recently, sensor arrays utilizing cross-reactive sensor

elements were developed.^{8–11} Such devices do not rely on selective sensors but on the analyte-triggered small perturbation arising from a large number of nonspecific sensors showing a wide range of interactions resulting in the formation of a pattern specific for a given analyte. The advantage of the cross-reactive arrays is in circumventing the difficulties associated with preparation of selective sensors, while taking advantage of random syntheses to generate large libraries of potential sensors.¹¹ Perhaps the most important feature of array-based pattern-recognition sensors is that they are amenable to identification and quantification of multicomponent analytes. This, however, requires a large number of sensors in an array and complex mathematical interpretation of the patterns.^{12,13} The

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sensors arrays were utilized in so-called artificial noses,¹⁴ tongues,^{15,16} and biochips, and were successfully used for the analysis of organic volatiles,¹⁷ beverages,¹⁸ proteins,^{19,20} nucleic acids,²¹ and biological fluids.²² Recently, efforts in sensor arrays development were mounted to lower the detection limits and increase sensitivity of methods for accurately quantifying the concentration of target analytes by employing specific recognition process in rationally designed multicomponent materials²³ and specificity of interactions between enzymes, antibodies, nucleic acids,⁸ or oligonucleotide three-way junctions and steroids.²⁴ Such methods, however, are not available for low-molecular targets such as anions. As a result, the arrays that distinguish among anions are rare.^{22,25}

Small inorganic anions are difficult to sense, particularly in water.²⁶ This is because anions are larger than isoelectric cations resulting in lower charge-to-radius ratio, a feature which makes the electrostatic binding of anions to the receptors less effective. Anions have a wide range of geometries and charge-delocalized forms, which requires higher design complexity of receptors and sensors required for successful sensing. Additionally, high free energy of solvation of anions implies that the receptors must compete more effectively with the medium. This aspect is particularly important in water.^{27,28} For example, fluoride with ionic radius of 1.33 Å has $\Delta G_{\text{hydration}} = -465$ kJ/mol, i.e., significantly greater than a potassium cation with almost the same size (1.38 Å) and $\Delta G_{\text{hydration}} = -295$ kJ/mol. All of these factors make sensing of anions a difficult task, and as a result, anion sensing is a great benchmark test for new sensing approaches.

In this study, we demonstrate the preparation of easy to use sensors and arrays for small inorganic anions that operate in water and in a multianion environment. We also demonstrate the utility of supramolecular observations of affinity and selectivity in the anion-sensor recognition process for the design of a high-resolution sensor array. Here, we use the sensor elements selective for particular analytes, for example fluoride and pyrophosphate, which also show significant cross-reactivity for other anions. The resulting array then utilizes the fluoride content as the main differentiating feature, while cross-reactive

elements in the array allow for fine differentiation among complex analytes.

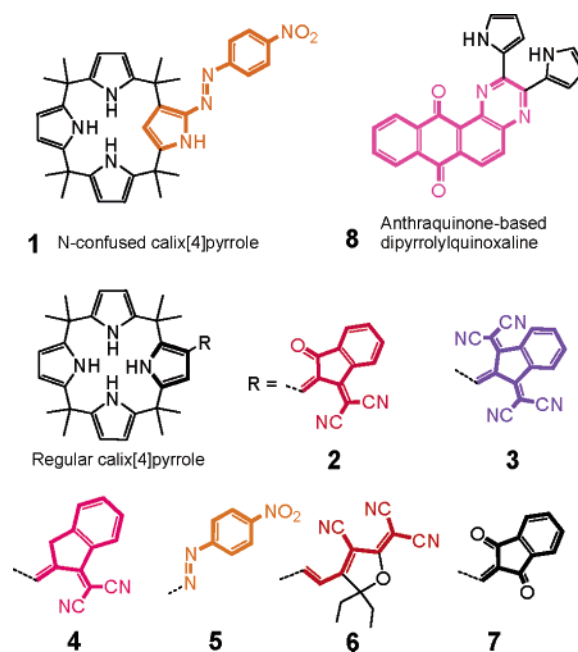
Experimental Section

The sensors were synthesized and their anion-binding properties investigated following the procedures described previously.^{29,31,32} The array chips were fabricated by ultrasonic drilling of microscope slides (well diameter, 500 ± 10 μm; depth, 500 ± 10 μm) to form an array of 8×10 wells. The wells were filled with 400 nL (approximately 0.08% sensor in polyurethane, w/w) in a Tecophilic THF solution (5% w/w) and dried to form a 10 μm thick polymer film in each well. In a typical assay, the anions were added as aqueous solutions (200 nL) of their TBA (tetrabutylammonium) salts. For the toothpaste analysis, 350 mg of toothpaste was added to 1 mL of water (Nanopure). The sample was sonicated for 1 h and centrifuged. Finally, the supernatant was filtered and added (200 nL) into the assay. At this concentration, the colorants added to the toothpaste are not registered by the image scanner. To bias the toothpaste samples, 2 mg of sodium fluoride was added to 1 mL of the supernatant of the toothpaste solution of Aquafresh, Colgate, and Crest. In the case of Fluoridex, 20 mg of Kryptofix[221] was added. The images were recorded by scanning the array slides using a USB flatbed scanner (Canon, CanoScan LiDE 60 at 1200 dpi resolution). Control experiments were carried out to confirm that at the used concentration the toothpaste color does not affect the reading from the scanner. Image processing is described in detail in the Supporting Information.

Results and Discussion

The sensor elements used in this study are eight sensors **1–8** forming an eight-member array. Sensors **1–8** are simple hydrogen-bonding-based anion sensors utilizing pyrrole hydrogen-bond donor moieties, such as N-confused calix[4]pyrrole²⁹ **1**, regular calix[4]pyrrole^{30,31} **2–7**, and 2,3-di(pyrrol-2-yl)quinoxaline³² **8**.

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Table 1. Affinity Constants for Compounds **1–8** (M^{-1}) Calculated for Tetra-*n*-butylammonium Salts of Anions in DMSO (0.5% Water) at 22 °C^a

sensor	$K_{\text{assoc}} [M^{-1}]$ for individual anions				
	F ⁻	Cl ⁻	AcO ⁻	H ₂ PO ₄ ⁻	HP ₂ O ₇ ³⁻
1	7240	<50	16 600	430	5650
2	> 10 ⁶	652	125 000	8050	274 000
3	> 10 ⁶	2840	> 10 ⁶	160 000	512 000
4	> 10 ⁶	759	22 100	5560	48 200
5	> 10 ⁶	741	8540	3330	92 200
6	> 10 ⁶	1900	99 900	7270	ND ^b
7	> 10 ⁶	574	15 700	4560	64 600 ^b
8^c	482 200	<50	1200	<100	316 000

^a All errors are <15%. ^b The binding isotherm showed biphasic behavior indicating multiple equilibria. ^c Affinity constants were obtained from experiments carried out in MeCN.

Because the substrate selectivity is related to high affinity, the analytes whose concentrations are exceedingly low are targeted by sensor moieties showing several orders of a magnitude higher affinity compared to the rest of the analyte. The respective affinity constants (Table 1) for sensors **1–8** were recorded in DMSO and MeCN solutions.^{29–32} In the following paragraphs, we show that the binding behavior observed in organic solvents is also observed in arrays when the sensor elements are embedded in polyurethane matrices and the anions are administered as strictly aqueous solutions. Thus, the classical methods of molecular recognition may be conveniently used to match the sensor–analyte pairs for array applications.

The relative affinity for sensor **1** is acetate > fluoride > pyrophosphate. Sensors **2–7** show an affinity order of fluoride > pyrophosphate ~ acetate and low affinity for phosphate, bromide, sulfate, and nitrate. In order to increase the selectivity in read-out information, we also included sensor **8**, which shows almost equal affinity for fluoride and pyrophosphate, and which does not bind any other anion strongly. One can see that the eight-sensor array composed of sensors **1–8** will have strong affinity bias for fluoride > pyrophosphate > acetate. Nevertheless, the sensors show cross-reactivity to other anions.

As previously reported,^{29–31} the change in color of all sensors upon complexation is a result of partial intramolecular charge transfer from the anion to the sensor. This is presumably due to perturbation of the HOMO energy levels of the sensors mainly localized on the pyrrole moieties. The presence of the anion raises the energy level of the HOMO causing a red shift in the absorption. However, the actual color change and dynamic range of the response differ among individual sensors, thus contributing to the cross-reactivity of the sensors.

The sensor elements for the arrays were fabricated by blending the sensors **1–8** with a polyurethane hydrogel in THF and solution-casting 400 nL of the sensor–polyurethane solution into a microwell array, *vide supra*. The role of the polyurethane hydrogel is to lend mechanical support to the sensor molecules and to draw the bulk aqueous analyte into the sensor material and partially strip the hydrate off the anion, thus rendering the anion available for the recognition process by the receptor moieties.³⁰

The qualitative response of sensors **1–8** was tested using aqueous solutions of 10 anions: acetate, benzoate, bromide, chloride, fluoride, nitrate, dihydrogen phosphate, hydrogen pyrophosphate, hydrogen sulfate, and hydrogen sulfide (Figure 1), (5 mM in water, 200 nL, 10 trials each, except nitrate and

hydrogen sulfate, 20 mM).³³ The color responses, which are observable by naked eye, were recorded using a USB 24-bit RGB scanner, the image was deconvoluted into RGB channels, and the gray pixel values³⁴ in each color channel were averaged and subtracted from the image taken before exposure (blank). Figure 1 shows color changes in the wells as well as the respective changes in the RGB values of sensors **1–8** upon addition of acetate.³⁵ Figure 1 (right panel) also shows the patterns generated from raw data in the green channel, which emphasizes what is clear from naked eye observation: the eight-sensor array is generating unique patterns for each anion. A concentration of 5 mM was selected because it results in saturation of most sensors in the array by all anions. The naked eye inspection confirmed that the wells showing the deepest changes in color were those of fluoride, pyrophosphate, and acetate. Further evaluation was performed by methods of multivariate analysis.¹²

The quantitative studies were also performed. While the majority of anions provide a response discernible by naked eye at 100 μ M concentrations and higher (Figure 2), the scanned images deconvoluted into the respective red–green–blue channels allow for constructing response isotherms from 0.2 to 360 ppm anions (10 μ M to 20 mM) (Figure 2). Figure 2, center, shows a quantitative representation of changes of the gray pixel value in the green channel of sensor **2** at acetate concentrations ranging from 10 μ M to 20 mM. From the inset in the graph, one can see that 90% of the change in the sensor response occurs between 0.1 and 1.8 ppm of acetate in water.

The dynamic range and magnitude of response of the individual sensor polymers correspond to the magnitudes of the affinity of the sensors to anionic substrates as reflected by the binding constants in organic solvents shown in Table 1. Hence, the analytes with lower target anion concentrations are better addressed by sensors showing higher binding constant and vice versa. This illustrates why it is important to tie the supramolecular behavior of the sensor elements, even though it was studied in organic solution, to the array response. Figure 2 shows the response of two sensors, **2** and **5**, to acetate in different concentration ranges. Here, sensor **2** reaches saturation at an acetate concentration below 10 ppm, while sensor **5** reaches saturation at a significantly higher concentration, *i.e.*, 300 ppm (>10 mM). Of course, this may not be such a surprise considering that sensor **2** shows a binding constant for acetate of ca. 100 000 M^{-1} , while sensor **5** displays a modest binding constant of less than 10 000 M^{-1} in DMSO.

The statistical evaluation of the array response to aqueous solutions of anions was further explored using principal component analysis (PCA) and hierarchical clustering analysis (HCA). PCA is a statistical treatment used to reduce a multidimensional data set for easier interpretation. This is achieved by calculating orthogonal eigenvectors (principal components, PC) that lie in the direction of the maximum variance within that data set. The first PC contains the highest degree of variance, and other PCs follow in the order of decreasing variance. Thus, the PCA concentrates the most significant characteristics (variance) of the data into a lower

(33) The concentration of 20 mM was used for nitrate and hydrogen sulfate as these anions gave somewhat ambiguous responses at 5 mM.

(34) The gray pixel value is a numerical value of the grey shade that for an 8-bit pixel depth detector ranges between 0 and 255.

(35) The Supporting Information lists the response profiles for all the analytes.

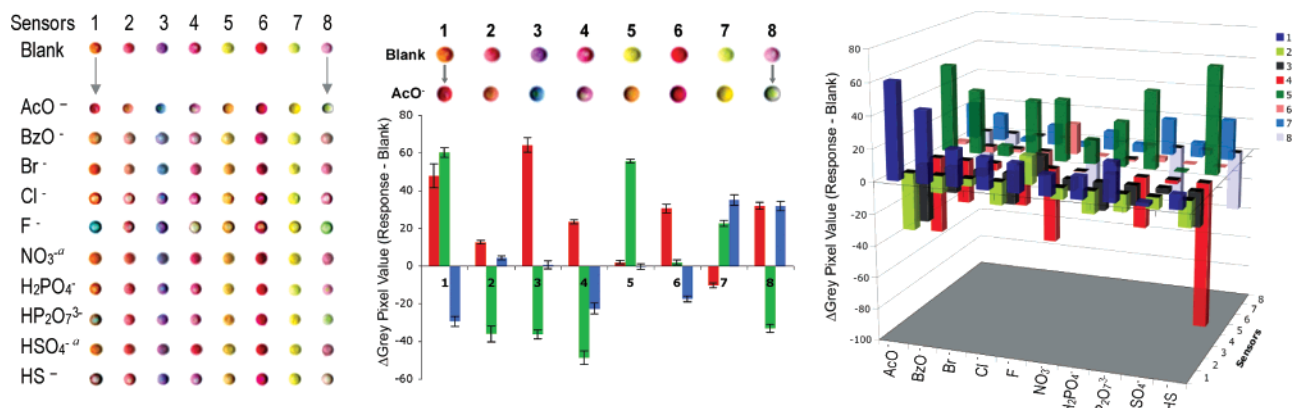


Figure 1. Left: Typical eight-sensor array responses (raw data) to aqueous anions solutions (200 nL, 5 mM; NO_3^- and HSO_4^- concentration was 20 mM) (ref 33). Center: The net response profile of sensors 1–8 to the addition of aqueous acetate (200 nL); the Supporting Information lists the response profiles for all analytes. Right: Patterns generated by the sensor array in the green channel in the presence of the same anion solutions as in the left panel.

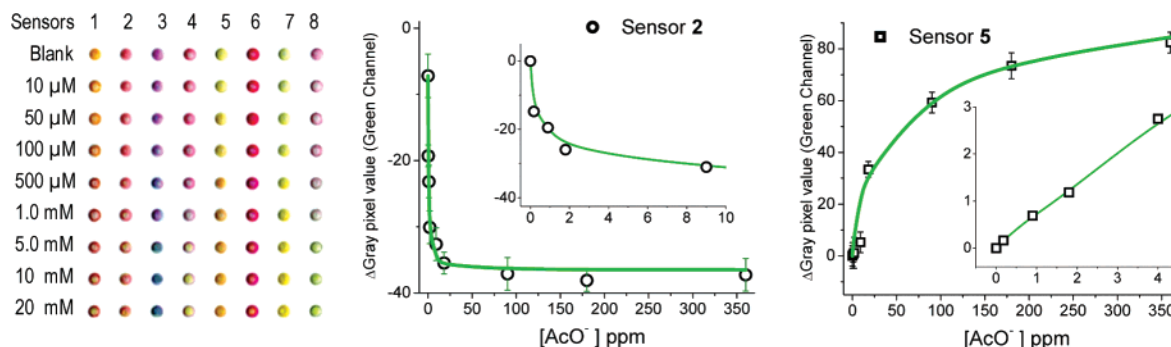


Figure 2. Left: Response of the eight-sensor array to different acetate concentrations. Center and Right: Changes in the gray pixel value (green channel) of sensors 2 and 5 upon increasing acetate concentrations.

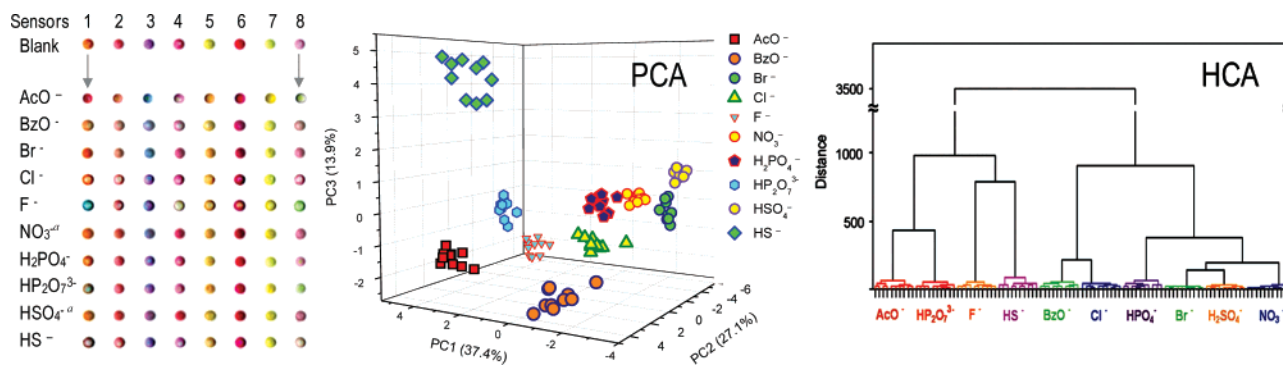


Figure 3. Left: Typical array responses (raw data) to aqueous anions solutions. Center: PCA score plot of the first three PCs for 100 samples (10 anions, 10 trials each) showing clear clustering of the trials. The percentages on the axes account for the amount of variance to each PC axis for a total of 78.4% of variance. Right: HCA dendrogram obtained using Ward linkage shows the Euclidean distance between the trials.

dimensional space. As articulated by Suslick and co-workers,^{18,36} generally the higher the number of PCs required to describe a certain level of discrimination, the better the sensor array discriminates between similar analytes. Here, the PCA of the data set (10 trials for each anion) obtained from the eight-sensor array requires 9 dimensions (PCs) out of 23 to describe 95% of the discriminatory range (39% of all PCs). This attests to an exceptionally high degree of dispersion of the data generated by this sensor array consisting of just eight sensor elements. This level of discrimination is in contrast to those reported for most electronic tongues, which have typically 95% of discrimi-

nation in the first two PCs.⁸ In addition, each pattern (24 dimensions, 8 sensors \times 3 RGB channels) generated by the eight-sensor array is reduced to a single score and plotted in the new space (PC space) generated using the PCs. This representation (score plot) is shown in Figure 3 (center). Here, the PCA score plot utilizes the first three PCs representing 78.4% of variance, and it already shows clear clustering of the data. More importantly, the high level of dispersion of the data shown by the PCA can be attributed to the selectivity of the sensors and a strong supramolecular interaction between the sensors and certain analytes (F^- , $\text{HP}_2\text{O}_7^{3-}$, AcO^- , and HS^-), while keeping a good degree of cross-reactivity (given by the observable colorimetric response even to the anions that show lower affinity

(36) (a) Suslick, K. S. *MRS Bull.* **2004**, *29*, 720–725. (b) Suslick, K. S.; Rakow, N. A. *Tetrahedron* **2004**, *60*, 11133–11138.

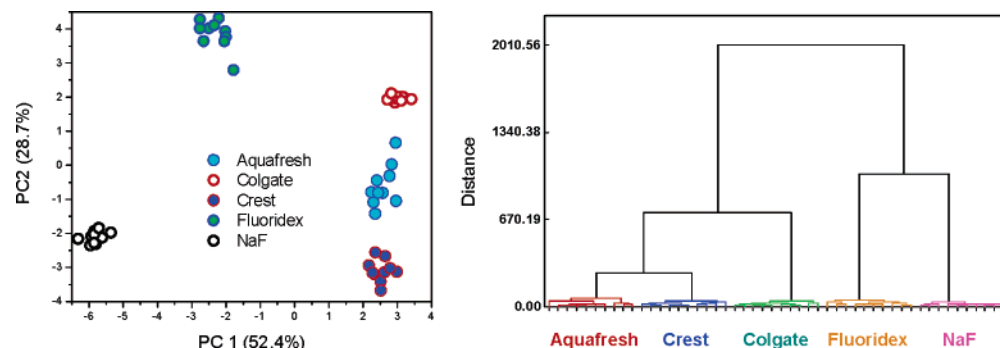


Figure 4. Left: PCA score plot of the first two PCs for 50 trials of four toothpaste brands and NaF (10 each) and the trial clustering. The percentages on each axis account for the variance intrinsic to the axis. Right: HCA dendrogram with Ward linkage showing the Euclidean distance between the trials.

for the sensors). This combination of a strong selective feature and high cross-reactivity allows for better separation (resolution) of the clusters in the PCA score plot.

The HCA, which is an unsupervised method of multivariate analysis, seeks classification of the samples by measuring the interpoint distances (in this study, the Euclidean distance) between all samples in the n -dimensional space resulting from n -numbers of studied features (e.g., 24 dimensions for our eight-sensor array). There are several methods for defining clusters.⁴ We used Ward's (minimum variance) method,³⁷ which takes into consideration the minimum amount of variance between the samples and analytes to define a cluster.³⁸

In contrast to PCA, HCA considers the complete dimensionality of the data and provides graphic output in the form of a dendrogram (Figure 3, right). At 90% of similarity, HCA shows 10 clusters, each comprising 10 samples. Interestingly, the HCA dendrogram shows clustering at approximately 1000 distance units (d.u.) for six anions: benzoate, chloride, phosphate, bromide, sulfate, and nitrate. This group of six anions are related by their similar relative affinity to calix[4]pyrrole derivatives **2–7** in organic solution (Table 1). Moreover, both acetate and pyrophosphate that show strong affinity toward the sensors in solution are also separated by a very short distance (approximately 500 d.u.), which reflects their similarity in interacting with the sensors.

Both PCA and HCA suggest that the sensor–hydrogel blends show similar supramolecular properties to the anion-binding characteristics observed in organic solution. Therefore, the solution-based observations performed by NMR, UV–vis, and fluorescence spectroscopy can aid in constructing arrays comprising sensors with predictable analytical behavior. Particularly, the connection between supramolecular properties (e.g., changes in conformation, binding stoichiometry, functional groups participation, and binding mode) on the atomic level observed by NMR and the discriminatory capability of the sensor array is important and cannot be easily established in arrays employing nonselective indicators.⁸ Two more aspects are worth noting: the sensing process is fully reversible, and the array is reusable.

To demonstrate the utility of substrate-selective sensors for anions in an array for complex analytes on a real-life example, we performed identification of toothpaste samples using fluoride/

pyrophosphate analysis. Toothpastes are very complex analytes composed of numerous known and unknown ingredients.³⁹ A typical toothpaste comprises abrasives (e.g., hydrated silica, calcium phosphate), fluoride sources (sodium fluoride, stannous fluoride, or sodium fluorophosphate), polymers to thicken the paste and retain moisture (carboxymethyl cellulose, polyethylene glycols), foaming agents (e.g., sodium dodecyl sulfate, sodium sarcosinate), tetrasodium pyrophosphate to remove Ca^{2+} and Mg^{2+} from saliva to prevent tartar calcification, whiteners (titanium dioxide), peroxide whiteners (sodium carbonate peroxide $2\text{Na}_2\text{CO}_3 \cdot 3\text{H}_2\text{O}_2$), sweeteners (sodium saccharin, xylitol), antibacterials (triclosan, zinc chloride), fragrances (e.g., peppermint, spearmint oils), sealants/sensitivity reducers (potassium nitrate, strontium chloride), preservatives (sodium benzoate, methyl paraben), buffering agents (sodium hydroxide), remineralization agents (calcium glycerophosphate, calcium ascorbate), etc. The approximate percentages of common ingredients are as follows: water and humectants 75%, abrasives 20%, foaming and flavoring agents 2%, buffering agents 2%, while fluoride is usually present in less than 0.25%. The fluoride content may differ significantly. Specialty toothpastes such as Fluoridex Daily Defense contain 1.1% NaF (5000 ppm).⁴⁰ This paragraph illustrates that a toothpaste is a complex analyte comprising fluoride, pyrophosphate, and large concentrations of other anions. Array elements operating in such an environment should show selectivity toward fluoride and pyrophosphate as well as cross-reactivity to distinguish among the brands based on other anionic components.

For our demonstration, we chose three toothpaste brands: Aquafresh, Colgate, and Crest, as well as Fluoridex and sodium fluoride for comparison. PCA and HCA were carried out for the data set generated by toothpastes with our eight-sensor array (Figure 4). The PCA score plot and HCA dendrogram for the 50 trials show clear clustering. Aquafresh, Colgate, and Crest appear to be more similar, and in the HCA they appear as one cluster at approximately 700 d.u., while Fluoridex forms a cluster with NaF at approximately 1000 d.u. Interestingly, the HCA dendrogram shows Colgate moderately dissimilar to Aquafresh and Crest within the same cluster. This could be

(37) Ward, J. H., Jr. *J. Am. Stat. Assoc.* **1963**, *58*, 236–244.

(38) For Ward's method first each sample is considered its own cluster; therefore, the variance is null. Then, each following step will consider a pair of objects that can be fused while keeping the amount of variance as small as possible. This process repeats until a remaining supercluster is formed.

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(40) Fluoridex, 2007; http://www.discussdental.com/products/oral_hygiene/fluorides.php?group_skey=4540.

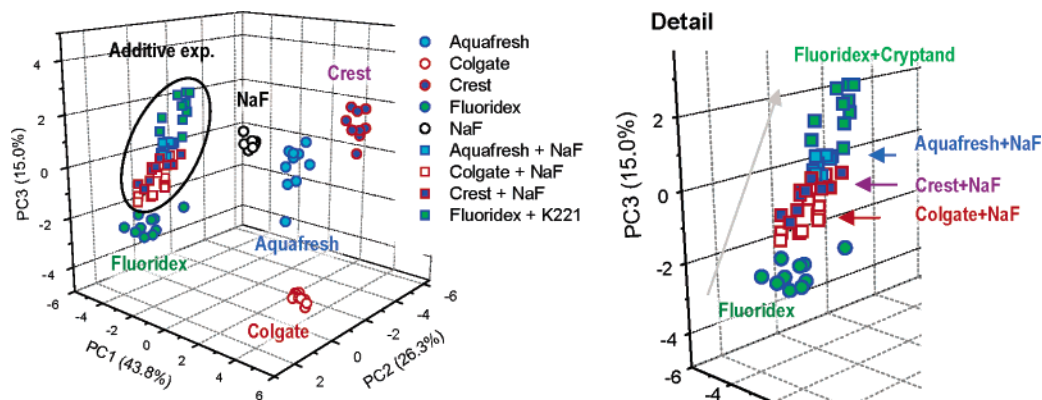


Figure 5. Left: PCA score plot for the four toothpaste brands and the results of the NaF addition experiments showing that the addition of fluoride to the toothpastes results in increased similarity in response as shown by the clustering. Addition of Na⁺-binding cryptand to Fluoridex generating more naked fluoride resulted in a response shift to the top of the NaF addition cluster (gray arrow).

attributed to the fact that Colgate is the only toothpaste in this study that lists pyrophosphate as an inactive ingredient (the Supporting Information lists all ingredients for the toothpastes used). This supports our hypothesis that using sensor elements of known selectivity, in this case fluoride and pyrophosphate, for the key analytes may allow for reducing the size of arrays while allowing for successful analysis of complex analytes.

To further support our hypothesis that fluoride is a major differentiation contributor to which the sensors react, we carried out control experiments by adding NaF to the less fluoridated toothpastes (Aquafresh, Colgate, Crest) and applied PCA to the data set obtained using toothpastes and toothpastes + NaF samples. Addition of NaF (to the level of 5000 ppm) resulted in a clear outcome on the PCA score plot (Figure 5): The NaF addition renders the three toothpastes more similar to Fluoridex (5000 ppm NaF). And, as the NaF addition renders the toothpastes more similar, the resulting clusters appear much closer to each other, although the array can still separate them.

A second control experiment further illustrates the role of fluoride in an array response. Since NaF is not highly dissociated, we added a small amount of [2.2.1]-cryptand to bind some sodium cations to generate more of the “naked” fluoride anion. The cryptand addition resulted in the shift of the Fluoridex cluster from the bottom of the group of clusters corresponding to the additive experiments (NaF + Aquafresh, NaF + Colgate, NaF + Crest) to its top (Figure 5, detail), confirming, once again, the major role of fluoride in the array response.⁴¹ A third control experiment was aimed at establishing the importance of selective array elements. Thus, we removed two of the most selective sensors, **8** and **1** or **8** and **7**, from the array. The array still showed reasonably good separation in the PCA score plot; however, the separation of the trial clusters was significantly less pronounced. Conversely, removing two of the less-selective sensors resulted in very little or no change in the array discriminatory capability. Altogether, the control experiments confirm that fluoride is a major factor the eight-sensor array reacts to, with the other anions further differentiating among the samples. This is what we predicted based on solution-based studies using sensors **1–8**, which are more selective for fluoride > pyrophosphate > carboxylates > other anions.

(41) The HCA dendrogram yields similar results; for more details refer to the Supporting Information.

In order to evaluate the overall discriminatory performance of the sensor array, we included all 190 samples corresponding to 19 analytes (anions, toothpastes, and toothpastes + NaF), as well as 10 samples with cyanide⁴² as an analyte that were included in the same data set, and the PCA was performed. This PCA requires 10 PCs out of 24 to describe the 95% of the variance (42% of the fraction of all PCs), which indicates that in the case when the number of analytes (and samples) is increased to 200, our eight-sensor array still shows the same high discriminatory capability.⁴³ For visualization of the clustering of the data, HCA analysis with Ward linkages was generated (see the Supporting Information). HCA shows clear clustering with 100% of classification for all analytes.

Conclusion

In summary, supramolecular eight-member sensor arrays were prepared by embedding simple colorimetric sensors in polyurethane hydrogel. The studies performed in organic solvents aimed at establishing the sensor–anion affinity and selectivity allow estimating the response of the array to aqueous anionic analytes. The clear connection between supramolecular observations in nonaqueous solutions and analysis of aqueous anionic samples in solid-state sensor arrays paves the road for using the numbers of the previously prepared sensors known from the literature, which, until now, could not be used due to low compatibility with the aqueous environment. Furthermore, this could be an important tool to consider in the rational design of minimal-size high-resolution arrays because it allows for designing arrays with predictable analytical behavior. The general utility of these principles was demonstrated on a simple eight-sensor array that was shown to differentiate between 10 inorganic anions and analyze toothpaste brands. This approach

(42) Cyanide samples were not included before because the response of the eight-sensor array is not completely reversible for the whole set of sensors in the presence of this anion.

(43) The “theoretical” discriminatory limit of a sensor array is given by the number of sensors in the array and the dynamic range of the detector. In the case of an array consisting in eight sensors (24 dimensions), where the grey pixel value has a range of 256 values (8-bit CCD), a sensor array should be able to generate up to 256^{24} patterns. A “practical” limit of discrimination (possible number of different patterns that the sensor array can possibly resolve) of our eight-sensor array can be estimated by considering that the changes of the grey pixel values for all sensors (RGB channels) in our data set average ~ 30 units and assuming that changes in at least five channels are needed to obtain a discriminatory pattern. PCA shows that 10 PCs can describe 95% of the discriminatory data. We estimate that our sensor array should be capable of discriminating between $(30/5)^{10} = 6^{10}$ patterns. This deduction of the practical discriminatory limit is adapted from the method proposed in ref 36b by Suslick and Rakow.

might be general and easily amenable to adaptation for other analytes and applications.

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Note Added after ASAP Publication. The wrong figure was cited in the first sentence of paragraph 11 of the Results and Discussion section in the version published ASAP May 27, 2007; the corrected version was published May 31, 2007.

Supporting Information Available: Detailed methodology, response profiles, and multivariate analysis. This material is available free of charge via the Internet at <http://pubs.acs.org>.

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