ACTIVE ODOR CANCELLATION

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ABSTRACT

Noise cancellation is a traditional problem in statistical signal processing that has not been studied in the olfactory domain for unwanted odors. In this paper, we use the newly discovered olfactory white signal class to formulate optimal active odor cancellation using both nuclear norm-regularized multivariate regression and simultaneous sparsity or group lasso-regularized non-negative regression. As an example, we show the proposed technique on real-world data to cancel the odor of durian, katsuobushi, sauerkraut, and onion.

***Index Terms*—** noise cancellation, olfactory signal processing, structured sparsity

1. INTRODUCTION

The origins of statistical signal processing are in canceling unwanted signals [1]; however the kinds of signals traditionally considered are from modalities such as speech, radar, and optics. There are often settings where chemical signals should be canceled: poor indoor air quality and malodors are not only a nuisance and source of dissatisfaction, but can decrease the productivity of office workers six to nine percent [2]. There are currently four general categories of techniques used for the reduction or elimination of odors: *masking*, which attempts to 'overpower' the offending odor with a single pleasant odor; *absorbing*, which uses active ingredients like baking soda and activated carbon; *eliminating*, in which chemicals react with odor molecules to turn them into inert, odorless compounds; and *oxidizing*, which accelerates the break-down of malodorous compounds. Here we consider using ideas of statistical signal processing instead.

To do so, we take advantage of the psychophysical properties of human end-consumers of odor. Human olfactory perception is synthetic rather than analytic, and so people do not combine smells of compounds through a weighting scheme in the perceptual domain but perceive the compound mixture's physicochemical representation [3]. In particular, there is a recently discovered percept called *olfactory white* which is the neutral smell generated by equal-intensity stimuli well-distributed across the physicochemical space [4], much like white light or auditory noise. Whiteness, too, is a central concept in active signal cancellation that can be performed by whitening followed by prediction on the residual innovations signal [5].

Here we develop a method for performing active odor cancellation, with some resemblance to active noise cancellation [6] or vibration cancellation [7]. As a preliminary step, we learn the mapping between the physicochemical description of odorants and their perceptual descriptions from a small amount of training data and nuclear norm regularization. This structure-odor mapping is used thereafter for computing an odor signal to cancel the sensed malodor by producing a synthetic percept of olfactory white. Physical devices used for actively producing odor signals are called *virtual aroma synthesizers* [8] and function by mixing compounds from several cartridges into an airstream, much like how inkjet printers produce arbitrary colors. It is costly to have many cartridges, and so we use structured sparsity regularization when designing the active odor cancellation system for several possible malodors.

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2. OLFACTORY PERCEPTUAL MAPPING

In this section, we describe a statistical methodology to learn a model for predicting olfactory perception from physicochemical properties based on existing perception and physicochemical data, which generalizes to chemical compounds and mixtures of compounds for which we do not know the olfactory perception. Human olfactory perception is difficult to pin down precisely; the most common technique used in the psychology and science literatures is to present an observer with a list of odor descriptor words or concepts and have him or her evaluate whether a given chemical's smell matches each odor descriptor. Averaging over many individual observers yields a real-valued odor descriptor space in which each chemical compound has coordinates. The physicochemical properties we consider are also numerical, so our goal is to learn a (generally nonlinear) functional mapping between the two spaces.

In this work, we restrict ourselves to linear mappings, the validity of which is suggested by human olfaction studies [9]. Moreover, in posing a multivariate linear regression problem, we impose a nuclear norm regularization term because human olfaction studies also suggest that the perceptual space is low-dimensional [10, 11]. Thus, given training samples of physicochemical features $\mathbf{x}_i \in \mathbb{R}^k$ labeled with their perceptual vectors $\mathbf{y}_i$, we would like to find the mapping $\mathbf{A}^* \in \mathbf{R}^{l \times k}$ that minimizes the objective:

$$\|\mathbf{Y} - \mathbf{A}\mathbf{X}\|_F + \lambda_1 \|\mathbf{A}\|_*, \tag{1}$$

where $\|\cdot\|_F$ is the Frobenius norm, $\|\cdot\|_*$ is the nuclear norm, λ_1 is a regularization parameter, and the $\mathbf{X}$ and $\mathbf{Y}$ matrices are concatenations of the training sample physicochemical and perceptual vectors [12].

3. OPTIMAL CANCELLATION MIXTURES

In the active odor cancellation applications of interest to us, several different malodors will be sensed and canceled by the same virtual aroma synthesizer. Therefore, in addition to providing excellent cancellation performance, we also desire the cardinality of the compound set in the system to be minimized. Toward this goal, we use the group lasso or simultaneous sparsity-inducing ℓ_1/ℓ_2 norm [13]. We also require a non-negativity constraint because optimized compound mixtures can only be output into the air, not subtracted [14]. Due to the synthetic nature of human olfaction, the generally nonlinear perceptual mapping (simplified to linear in this paper) is applied

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to the physicochemical representation of mixtures of compounds exhaled by the system.

As a starting point, we collect a set of n compounds that could possibly be used in the aroma synthesizer. Let the physicochemical representation of this dictionary be $\mathbf{X}_{\text{dict}} \in \mathbb{R}^{k\times n}$. We would like to design the system to optimally cancel m different malodors with perceptual representations $\mathbf{Y}_{\text{mal}} \in \mathbb{R}^{l\times m}$. We would like to determine a simultaneously sparse set of non-negative coefficients $\mathbf{W}^* \in \mathbb{R}^{n\times m}$ that minimize:

$$\tfrac{1}{2}\|\mathbf{Y}_{\text{mal}} + \mathbf{A}^*\left(\mathbf{X}_{\text{dict}}\mathbf{W}\right)\|_F^2 + \lambda_2\|\mathbf{W}\|_{1,2}, \quad \text{s.t. } \mathbf{W} \geq 0, \qquad (2)$$

where λ_2 is a regularization parameter, and the ℓ_1/ℓ_2 norm takes ℓ_2 norms of each of the n length-m rows of $\mathbf{W}$ first and then takes the ℓ_1 norm of the resulting length-n vector.

4. EXAMPLE

In this section, we present an empirical example of active odor cancellation that may arise in the break room or lunch room of a small office. We consider $m = 4$ different offending odors that we wish to cancel with the same, small-cardinality set of olfactory compounds. The four smells are: durian (Durio zibethinus), onion (Allium cepa L.), katsuobushi (dried bonito), and sauerkraut. With an optimal solution to the problem, we can create a device with minimal complexity that senses the current odor and outputs the appropriate concentrations of compounds to cancel it. When placed in the break room, the device will be able to cancel these four odors, but also many others.

The first step in our empirical study is to learn a mapping from physicochemical properties of compounds to the olfactory perception of those compounds. We collect a ($k = 18$)-dimensional physicochemical feature vector for each of 143 different chemical compounds that have been judged by human observers against $l = 146$ different odor descriptors as diverse as 'almond,' 'cat urine,' 'stale tobacco smoke,' and 'violets.' The 18 physicochemical features are obtained from the National Center for Biotechnology Information's PubChem Project and include among others: topological polar surface area, molecular weight, complexity, heavy atom count, hydrogen bond donor count, and tautomer count. The human judgements on odor descriptors are obtained from the Atlas of Odor Character Profiles [15]. We learn the mapping by solving the nuclear norm-regularized multivariate linear regression problem discussed in Section 2 using the method of [12]. We conduct five-fold cross-validation to determine the best value of λ_1. As a figure of merit, we consider the root mean squared error (RMSE) averaged over the 146 dimensions; Fig. 1 shows the cross-validation testing average RMSE as a function of λ_1. The error is minimized at approximately $\lambda_1 = 10^4$ and is the value we use going forward.

The perceptual representation of the four odor mixtures of interest can be predicted from the learned mapping. First, in the same spirit as the synthesis that takes place in human olfactory perception, we take a linear combination of the physicochemical features of the components of the odor and then map the resulting physicochemical vector to perceptual space. Linear combination with concentrations as the mixture weights is an acceptable first-order approximation although concentration is mediated by some other effects, such as water solubility, in impact on olfactory intensity [16]. We obtain the set of olfactory compounds present in the four odors and their concentrations from the Volatile Compounds in Food 14.1 database (VCF) and obtain physicochemical features of those compounds from PubChem. The resulting predicted perceptions of durian, katsuobushi, sauerkraut, and onion are shown in Fig. 3. For example, it can be seen in the figure that sauerkraut is perceived most like the 'oily, fatty' descriptor and least like the 'fruity, citrus' descriptor.

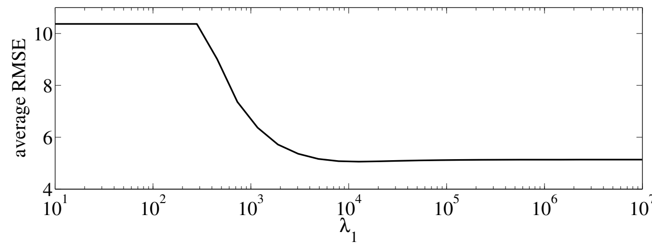

Fig. 1. Five-fold cross-validation testing root mean squared error of the mapping between physicochemical and perceptual spaces averaged across the 146 perceptual dimensions.

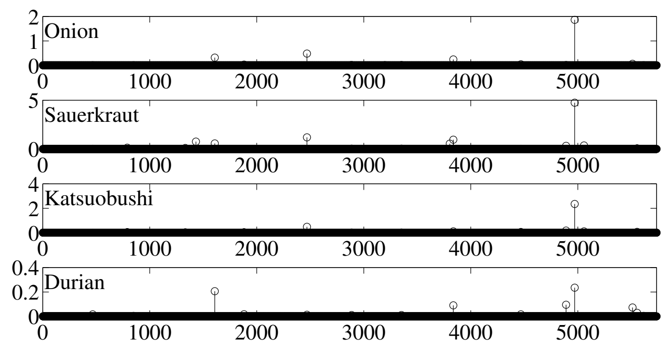

Fig. 2. Dictionary coefficient values in optimal cancellation solution with $\lambda_2 = 1$.

Having predicted the perception of the four odors of interest, the next step is to find compounds that can be used to cancel their smells perceptually. Toward this end, we first construct a dictionary of compounds from which we can find the cancellation set. We extract $n = 5736$ compounds from VCF found naturally in food and find their physicochemical properties from PubChem. This dictionary, with members only from natural edible products has certain limitations, which we comment on later. We use the non-negative simultaneous sparsity formulation given in Section 3 with this dictionary to find the optimal sparse set of compounds for active odor cancellation with different values of the regularization parameter λ_2. We use SDPT3 to solve the optimization problem [17].

The set of coefficients $\mathbf{W}^*$ found for $\lambda_2 = 1$ is shown in Fig. 2. There are 22 compounds with positive coefficient value in at least one of the four cancellation additives. The residual odor remaining after cancellation is shown in Fig. 4. The Frobenius norm of the residual is 17.13 and the ℓ_2 norms of the individual odors are 1.41 for durian, 4.38 for katsuobushi, 16.30 for sauerkraut, and 2.50 for onion. By reducing λ_2, we can improve the cancellation at the expense of increasing the number of compounds used. The coefficients in the optimal solution for $\lambda_2 = 0.25$ are shown in Fig. 5 and the residual perception in Fig. 6. In this solution, 38 compounds have positive coefficients and the Frobenius norm of the residual is 2.30. Residual ℓ_2 norms of individual odors are: durian 0.04, katsuobushi 0.12, sauerkraut 2.29, and onion 0.24.

The $\lambda_2 = 1$ solution does provide a certain level of odor cancellation, but just by decreasing the sparsity a little bit, we are able to get very good cancellation. Only the residual of sauerkraut is non-

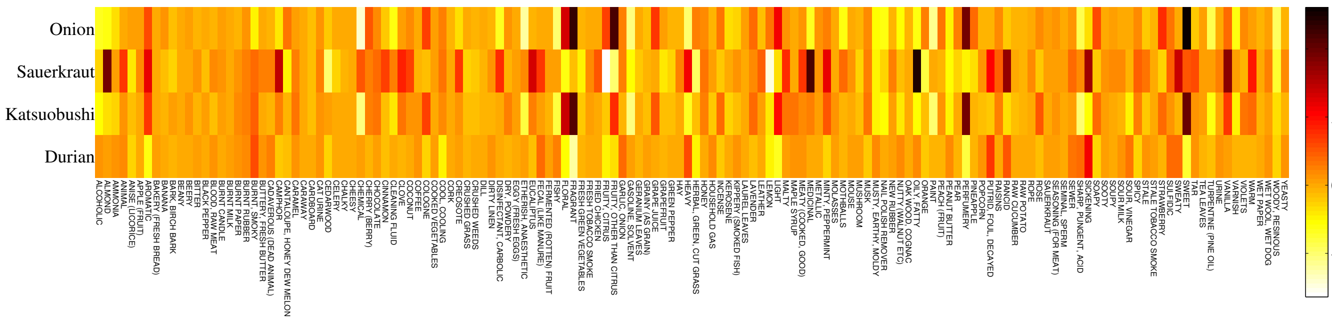

Fig. 3. Perceptual projection of the mixture of compounds contained in durian, katsuobushi, sauerkraut, and onion.

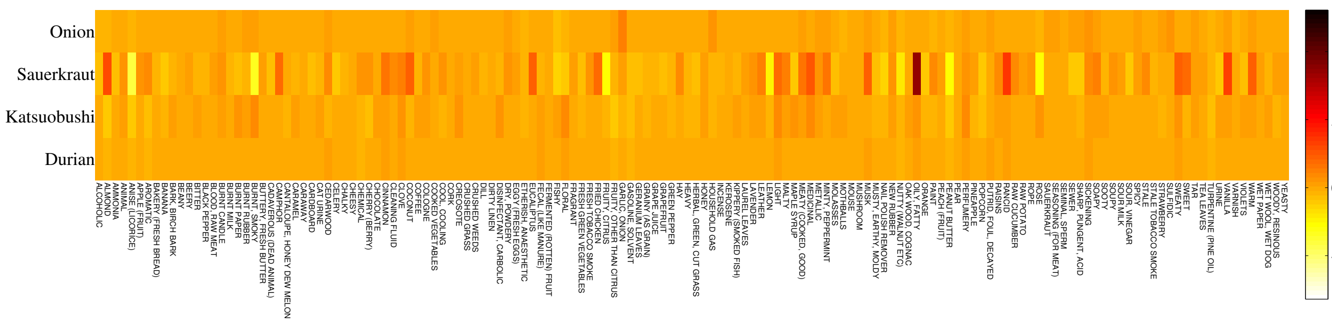

Fig. 4. Perceptual representation of residual odor after cancellation of durian, katsuobushi, sauerkraut, and onion with $\lambda_2 = 1$.

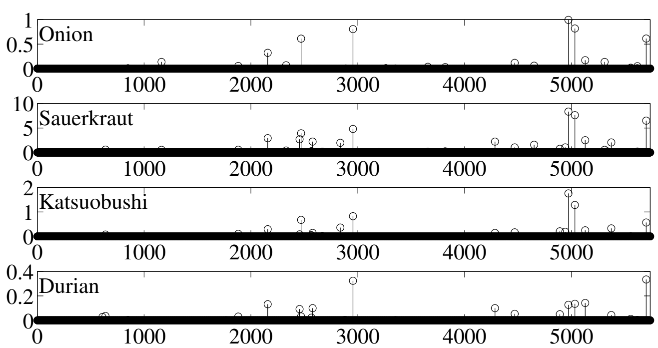

Fig. 5. Dictionary coefficient values in optimal cancellation solution with $\lambda_2 = 0.25$.

negligible in the $\lambda_2 = 0.25$ solution, and even that is nearing negligibility. We note that certain parts of the various odor signatures are easier to cancel than others. For example, the descriptor 'medicinal' is mostly removed from the sauerkraut solution with $\lambda_2 = 1$ but 'eucaliptus' is not. With a limited budget on their number, compounds that affect all four odors are at a premium. Thirteen compounds (out of 22 and 38, respectively) are common to the two solutions: '(+)-cyclosativene,' '(E,E,Z)-1,3,5,8-undecatetraene,' '(R)-3-hydroxy-2-pentanone,' '1,3,5,8-undecatetraene,' '10-methyl-2-undecenal,' 'cis-piperitol oxide,' 'cubenene,' 'cyclooctatetraene,' 'dehydrocurdione,' 'ethylpyrrole (unkn.str.),' 'heptatriacontane,' 'juniper camphor,' and 'methane.'

As discussed in Section 1, our formulation of active odor cancellation is associated with the concept of olfactory white, which emerges with around thirty (but not with fewer) compounds of equal intensity covering the space of compounds fairly evenly. We visualize the space of compounds using the first two principal components of the perceptual vectors of the compounds in the dictionary and the four odors under consideration in Fig. 7. The compounds with non-zero coefficient values do span the space as best as they can to produce something akin to olfactory white. It is interesting to note that the modest increase from 22 to 38 compounds yields such a large improvement in cancellation quality where these two values are on either side of the number required for olfactory white. In the visualization, we also see that the dictionary we have used does not well-cover the full space; this is partly because the only compounds we have used are present in food products, suggesting that for improved cancellation, we should consider a more diverse dictionary that covers the space of olfactory perception better.

5. CONCLUSION

New developments in the science of smell are starting to lay the foundations for us to build signal processing techniques upon. This paper represents a first foray into this new domain for statistical signal processing. By addressing one of the fundamental problems of signal processing, noise cancellation, this work opens up a new category of techniques for dealing with bad odors beyond masking, absorbing, eliminating, and oxidizing. The most important application is to indoor air quality.

Having investigated olfactory whiteness and cancellation, a next step is to consider more general filtering operations with desired output odors. We can also consider canceling and filtering time-varying odors with predictable dynamics such as may arise in the air quality of a traveling automobile. There is much potential scope for olfac-

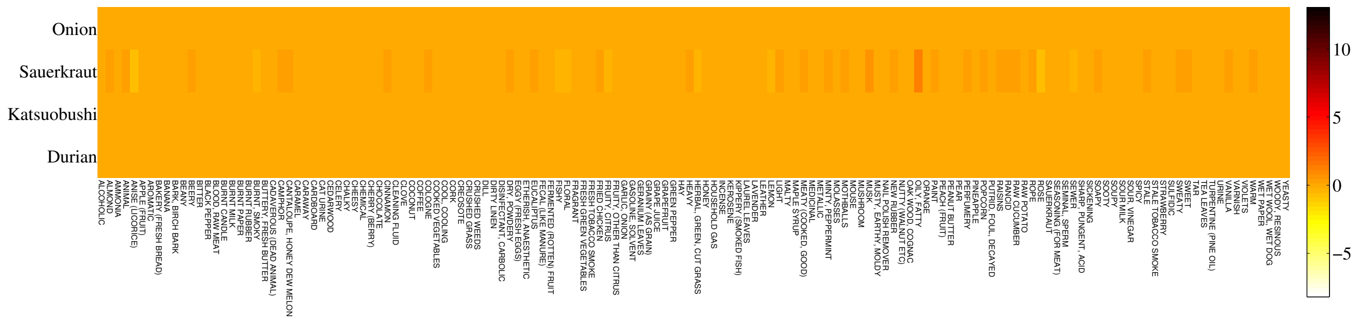

Fig. 6. Perceptual representation of residual odor after cancellation of durian, katsuobushi, sauerkraut, and onion with $\lambda_2 = 0.25$.

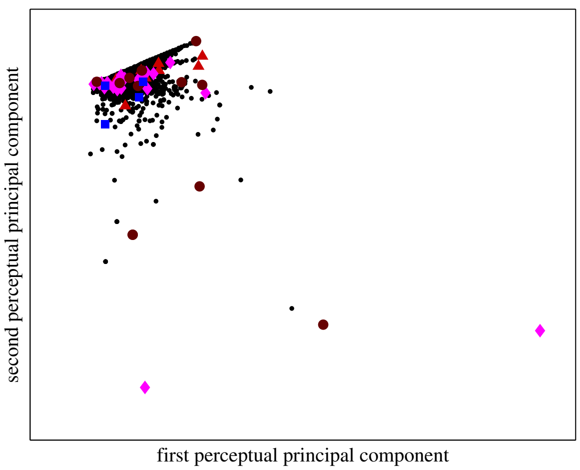

Fig. 7. Principal component projection of perceptual vectors of dictionary and four odors. The blue squares are the four odors to be canceled, the red triangles are compounds selected only in the $\lambda_2 = 1$ solution, the magenta diamonds are compounds selected only in the $\lambda_2 = 0.25$ solution, the maroon circles are the compounds selected in both the $\lambda_2 = 1$ and $\lambda_2 = 0.25$ solutions, and the black points are all other compounds in the dictionary.

tory signal processing research in the future.

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