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Olfactory signal processing ☆

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ABSTRACT

Olfaction, the sense of smell, has received scant attention from a signal processing perspective in comparison to audition and vision. In this paper, we develop a signal processing paradigm for olfactory signals based on new scientific discoveries including the psychophysics concept of *olfactory white*. We describe a framework for predicting the perception of odorant compounds from their physicochemical features and use the prediction as a foundation for several downstream processing tasks. We detail formulations for odor cancellation and food steganography, and provide real-world empirical examples for the two tasks. We also discuss adaptive filtering and other olfactory signal processing tasks at a high level.

1. Introduction

Audition, vision, and olfaction are the three ways that people remotely sense stimuli; much signal processing research has dealt with audio and video signals, but study of olfactory signal processing has been neglected. One reason is the difficulty in compactly specifying the fundamental inputs to the human perceptual system. Whereas vibration and light signals interacting with the ears and eyes are compactly parameterized by amplitude, phase, and frequency, olfactory signals interacting with the nose manifest as collections of chemical compound molecules drawn from a very large set. Despite the possible input set having very large cardinality, recent evidence suggests that the space of olfactory perception is fairly low-dimensional [3–5]. The most basic dimension, akin to the DC component of a waveform, is *pleasantness* [6,7]. Another recent finding shows the existence of *olfactory white* in human psychophysics with similar perceptual properties as white light and white audio signals [8].

In this paper, we investigate olfactory signals and systems at a level of abstraction removed from the physical sensing and actuation of chemical compounds. Prior work in olfactory signal processing at the lower physical level includes the following. One longstanding area of research has been developing chemical sensors and so-called *electronic noses*, see e.g. [9–11], references therein and thereto. A variety of sensing technologies including chemical gas sensors, optical sensor systems, infrared spectroscopy, and microelectromechanical sensors have been developed, and the signal processing and machine learning challenge is using raw sensor data to identify the specific composition of compounds present, cf. [12–14]. Gas chromatography mass spectrometry is considered the gold standard in laboratories, but the goal is to make portable, low-power, and low-cost systems with similar performance. In all such systems, human perception is not considered and the goal is simply to classify according to physicochemical properties [15].

Moving from sensors to actuators, physical devices used for actively producing odor signals are called *virtual aroma synthesizers* [16] and function by mixing compounds from several cartridges into an airstream, much like how inkjet printers produce arbitrary colors. These devices have been put together in a variety of old and new odor communication technologies [17,18]. Classical examples like AromaRama and Smell-O-Vision attempted to enhance the experience of cinema viewers through a greater degree of immersion, whereas modern examples like oPhone aim to enable multi-odiferous messages transmitted to individuals. With the practice of olfactory communication, there is also an information theory of olfaction concerned with bounding the human capacity to perceive and differentiate odors [19,20].

There has been much new understanding of olfactory perception and many new developments in the science of smell, see e.g. [21], which in contrast to the low-level signal processing described above, is what we build upon in this work. An important finding is that the full gamut of odor perception for a compound or mixture of compounds (including pleasantness and whiteness) can be predicted from the physicochemical properties of the molecules [22], in part via information processing models

☆ Portions of the material in this paper were first presented in [1] and [2].

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of cortex [23]. Moreover, human olfactory perception is primarily synthetic rather than analytic. What this means is that when people smell mixtures of compounds, they do not perceive a mixture of individual compound percepts. Instead, they perceive a single physicochemical object all at once, where that single physicochemical object is a weighted combination of the individual physicochemical features of the compounds in the mixture.

One may ask how the olfactory perception space is represented. Experiments have human subjects describe the smell of pure chemical compounds in words—tolualdehyde smelling 'fragrant,' 'aromatic,' 'almond,' and 'sweet;' or valeric acid smelling 'rancid,' 'sweaty,' 'putrid,' 'fecal,' and 'sickening' [24]—resulting in a perceptual space whose dimensions are these odor descriptors. By averaging odor descriptor judgments over several subjects, each compound can be placed as a point in a real-valued perceptual space where the coordinate value is a function of the percentage of subjects who use a descriptor for a compound. Such experiments have only been conducted on a small set of compounds, but we estimate the perception of uncharacterized compounds and mixtures from their physicochemical structure represented as a vector of features describing the molecule.

In particular, we learn the mapping between the physicochemical description of odorant compounds and their perceptual descriptions from a small amount of training data so it generalizes to all compounds. We pose the learning problem as one of multivariate regression. Our training set includes odor descriptor data (labels) and physicochemical data (features) from the small subset of compounds for which experimentally-determined odor descriptors exist. As it is believed olfactory perception is fairly low-dimensional, we use nuclear norm regularization to keep the rank of the estimated mapping operator small [25].

An aspect of odor perception not yet fully resolved in the literature is how perceived odor *intensity* is determined by the concentration and molecular properties of compounds and the medium in which they are suspended [26]. We use straightforward concentration as an acceptable first-order approximation [27].

Given recent scientific progress on understanding olfactory perception, the time is ripe to develop engineering theories and technologies that build upon the science for applications in indoor air quality [28,1], virtual reality [17,18], culinary arts[1] [30,2,31,32], hunting [33], and numerous others. In this work, our contribution is to take a statistical signal processing perspective on systems involving olfaction and develop the basic tools needed to engineer them. Upon showing how to learn the olfactory physicochemical–perceptual mapping, we develop specific example designs for problems of *active odor cancellation* [1] and *food steganography* [2], and discuss many other olfactory operations at a high level, including filtering and smoothing, enhancement, lossy compression, communication and storage, and retrieval. As far as we know, there is no prior work on active odor cancellation or olfactory steganography.

The remainder of this paper is organized as follows. In Section 2, we describe the common first step for olfactory signal processing of learning the mapping between the physicochemical and perceptual spaces. We detail the formulation of one example olfactory signal processing system, active odor cancellation, in Section 3 and another, food steganography, in Section 4. We provide high-level views on several other systems involving olfactory signals in Section 5. Section 6 presents empirical studies on learning, cancellation, and steganography. Finally, Section 7 summarizes the work and presents an outlook of future work in this area.

[1] The primary contributors to human flavor perception are retronasal and orthonasal smell [29].

2. Learning the mapping between physicochemical and perceptual spaces

The guiding principle of psychophysics, verified over centuries of experiments with human subjects, is that the physical properties of a stimulus largely determine its percept. For olfactory signals, we assume there is some general nonlinear mapping from the physicochemical attributes of a compound to its perceptual odor description. In this section we develop a statistical methodology to learn a generalizable mapping from molecular structure of compounds to their percept. The goal is to estimate the perceptual representation of compounds and mixtures of compounds for which no experimental ground truth on perception exists, but for which physicochemical properties are readily available.

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 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 [6]. (More complex mappings, including polynomial mappings suggested in [4] and kernel-based mappings [34], can be accomodated in the same type of linear model described below.)

Thus, we are given a set of training samples $\{(\mathbf{x}_1, \mathbf{y}_1), \ldots, (\mathbf{x}_n, \mathbf{y}_n)\}$ where the $\mathbf{x}_i \in \mathbb{R}^k$ are physicochemical features of compounds and the $\mathbf{y}_i \in \mathbb{R}^l$ are the perceptual vectors in the odor descriptor space. Desiring a low-dimensional mapping, we use nuclear norm-regularized multivariate linear regression to learn a matrix $\mathbf{A}^* \in \mathbb{R}^{l \times k}$ that maps unseen compounds from the chemical to the perceptual space. In particular, if we concatenate all the training samples into matrices $\mathbf{X} \in \mathbb{R}^{k \times n}$ and $\mathbf{Y} \in \mathbb{R}^{l \times n}$, the problem to solve is:

$$\mathbf{A}^* = \arg\min_{\mathbf{A}} \|\mathbf{Y} - \mathbf{A}\mathbf{X}\|_F + \lambda \|\mathbf{A}\|_* \qquad (1)$$

where λ trades data fidelity for sparsity of the singular values of $\mathbf{A}^*$. This problem is convex and can be solved by interior point methods and a variant of Nesterov's smooth method [25].

Note that Euclidean norms make sense as both optimization objectives (Frobenius norm) and characterizations of system performance (RMSE), since they are used in olfactory psychophysics studies with human subjects from several different laboratories [4, 5,22,35], and in the recent DREAM Olfaction Prediction Challenge, a part of the Rockefeller University Smell Study.[2]

3. Active odor cancellation

Noise cancellation is one of the most basic of signal processing tasks [36,37], and thus we use it as the first task within which to describe olfactory signal processing. 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 [28]. Four general categories of techniques are currently used for reducing or eliminating 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

[2] https://www.synapse.org/#!Synapse:syn2811262.