FOOD STEGANOGRAPHY WITH OLFACTORY WHITE

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ABSTRACT

Can one hide an averse food in a flavorful food so that the averse food is not perceptible? Here we take a statistical signal processing approach to show how to optimally design a food additive (either using pure flavor compounds or natural ingredients) to act as a steganographic key for this food steganography problem. We use a synthesis-based model of olfaction that has emerged in the psychology literature and the percept known as *olfactory white* acts as an intermediate signal in our approach. The problem decomposes into predictive analytics and prescriptive analytics components. In the predictive component, we learn a mapping from the space of physicochemical descriptors of flavor compounds to the space of perceptual odor descriptors through multivariate regression with nuclear norm regularization. In the prescriptive component, we find optimal mixtures of compounds or foods to make the averse food imperceptible in the flavorful food by posing and solving an inverse problem with non-negativity constraints. We demonstrate the proposed approach on real-world physicochemical and olfactory perception data for compounds in food.

Index Terms— olfactory signal processing, steganography

1. INTRODUCTION

Properties of human perception have frequently been used to design image processing and audio processing systems that have people as end users of light and vibration signals. However, signal processing for olfactory signals is in an incipient stage; 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. Although the possible inputs are nearly countably infinite, evidence suggests that the space of olfactory perception is fairly low-dimensional [1, 2] due to the nature of cortical signal processing [3].

Moreover, there has been a recent finding that a *white* olfactory percept exists in human perception with a similar connotation as white light and white audio signals [4]. A white odor is one that has equal amplitude across all olfactory perception dimensions, similar to white light having equal amplitude across all frequencies. While there are many promising directions to pursue in olfactory signal processing, in this paper we focus on steganography, the very old concept of imperceptibly hiding a signal into a cover medium [5–7]. More specifically, we develop a methodology for hiding one food into another food. (Human flavor perception involves a variety of external sensory stimuli and internal states, but the smell of foods is the key contributor [8]. Thus, we only consider the olfactory properties of the chemical compounds in food.)

*Work performed while with IBM Research.

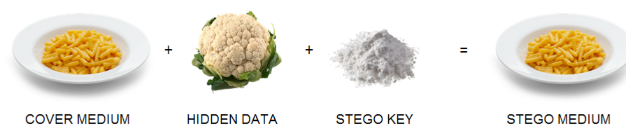

Fig. 1. Depiction of food steganography in the perceptual domain, where macaroni & cheese is delectable, cauliflower is averse, and the white powder is the additive.

There are many possible goals in steganography; here, the goal is not for the receiver to decipher a hidden message, but only to make imperceptible a food to which the receiver is averse (and which may have good nutritional properties). Many children, as well as adults, are picky eaters to whom junk food is more attractive than healthy food. This instinct was useful for hunter-gatherers that depended heavily on their senses to decide what to eat: in nature, foods that are sweet are almost always safe to eat and are nutritious. Foods that smell odd are potentially toxic or spoiled and less safe. In the modern environment, this same instinct often serves to make people obese and chronically ill. Therefore, if we can hide a nutritious averse food in a delectable food, we can aid people in eating healthier. The steganographic percepts are depicted in Fig. 1.

The proposed food steganography method shares characteristics with spread spectrum image steganography [9]. A food additive (steganographic key) combines with the averse food (hidden signal), and the delectable food (cover medium) such that the combination is perceived as only the delectable food's flavor; the olfactory white signal is used as a mathematical intermediary. The food additive may be composed of some weighted mixture of pure compounds or some weighted mixture of food ingredients from a dictionary. We may also want to regularize the problem by including a sparsity or other cost-related penalty on the food additive.

Difficulty lies in working with the olfactory perception space. Human experiments have been conducted in which subjects describe the smell of pure chemical compounds in words, e.g. tolualdehyde smelling 'fragrant,' 'aromatic,' 'almond' and 'sweet,' and valeric acid smelling 'rancid,' 'sweaty,' 'putrid,' 'fecal' and 'sickening' [10], resulting in a perceptual space whose dimensions are these odor descriptors. By averaging odor descriptor judgements over several subjects, each compound can be placed as a point in this real-valued perceptual space. Unfortunately, such experiments have only been conducted on a small subset of flavor compounds found in foods. Recent work, however, demonstrates the possibility of predicting perceptual similarity of flavor compounds by their physicochemical structure [11], allowing us to estimate the perception of uncharacterized compounds and mixtures.

The components of the proposed food steganography method are summarized as follows. First, from a small subset of compounds for which experimentally-determined odor descriptors exist, we use

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odor descriptor data and physicochemical data to estimate a mapping from a compound's structural properties to its perceptual properties; as it is believed that olfactory perception is fairly low-dimensional, we use nuclear norm regularization to keep the rank of the estimated mapping operator small [12]. Using data on the concentrations of flavor compounds in foods, we take a weighted combination of the physicochemical vectors of the constituent compounds of a food to determine its perceptual representation, using the learned mapping. Next, we solve a regularized inverse problem with a non-negativity constraint to find compounds or foods and their coefficients required to synthesize an additive that produces olfactory white when combined with an averse food of interest.

2. MAPPING FROM PHYSICOCHEMICAL TO PERCEPTUAL SPACE

The guiding principle of psychophysics is that the physical properties of a stimulus determine its percept. This is also true for olfactory signals: there is some general nonlinear mapping $A(\cdot)$ from the physicochemical attributes of a compound $\mathbf{x}$ to its perceptual odor description $\mathbf{y}$, $\mathbf{y} = A(\mathbf{x})$. In this section we develop a way to learn the mapping from molecular structure of flavor compounds to their percept. The goal is to estimate the perceptual representation of compounds for which no experimental ground truth on perception exists, but for which physicochemical properties are readily available.

When learning the structure-odor mapping, we restrict attention to multivariate linear mappings since studies of human olfaction suggest the validity of a linear approximation [13]. Further, we apply a nuclear norm regularization as part of learning, since studies suggest human olfaction is low-dimensional [1, 2, 13, 14] due to the nature of neural circuitry that performs olfactory signal processing in the brain [3]. We treat this learning problem as one of supervised multivariate linear regression [12].

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. We learn a matrix $\mathbf{A}^* \in \mathbb{R}^{l\times k}$ that maps unseen compounds from the chemical to the perceptual space. For the purpose of generalization, we regularize the problem using the nuclear norm. 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:

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

where $\|\cdot\|_F$ is the Frobenius norm, $\|\cdot\|_*$ is the nuclear norm, and 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 [12].

Going forward we use $\mathbf{A}^*$ as the learned linear structure-odor mapping $A(\cdot)$.

3. DETERMINING THE STEGANOGRAPHIC KEY

The mapping was learned from data on individual compounds, but how should we treat mixtures of compounds as present in food ingredients? (There are typically tens to hundreds of different chemical compounds contributing to flavor per food ingredient.) The human brain processing mechanism in olfaction is thought to be synthetic rather than analytical, and so smells of compounds are not combined through a weighting scheme in the perceptual domain but rather the combined compound mixture's physicochemical representations are mapped to a percept. We make a simplifying linearity assumption that the percept is $A\left(\sum_{j=1}^m w_j \mathbf{x}_j\right)$. The weights w_j are determined by the perceived intensities of the individual compounds in addition to their concentrations. The nonlinear psychophysical law that maps concentration to intensity is modulated by factors such as the compound's water solubility [15].

Let $\mathbf{X}^{(g)}$ be the physicochemical representation of the cover medium's compounds and $\mathbf{w}^{(g)}$ be the weights of the cover medium's compounds. Likewise let us introduce $\mathbf{X}^{(h)}$ and $\mathbf{w}^{(h)}$ for the hidden data. Let $\mathbf{X}^{(f)}$ be a dictionary of possible compounds or compound mixtures from which we can construct the steganographic key (food additive) along with its weight vector $\mathbf{w}^{(f)}$ which is the subject of design. With this notation, the perceptual hiding we want to perform is to choose $\mathbf{w}^{(f)}$ to satisfy:

$$A\left(\mathbf{X}^{(f)}\mathbf{w}^{(f)} + \mathbf{X}^{(g)}\mathbf{w}^{(g)} + \mathbf{X}^{(h)}\mathbf{w}^{(h)}\right) \approx A\left(\mathbf{X}^{(g)}\mathbf{w}^{(g)}\right). \tag{2}$$

For general nonlinear structure-odor maps $A(\cdot)$ we would need to appeal to the concept of olfactory white, the perceptual "zero-point," to make progress towards this objective. With a linear mapping, however, the objective simplifies to:

$$\mathbf{A}\mathbf{X}^{(f)}\mathbf{w}^{(f)} \approx -\mathbf{A}\mathbf{X}^{(h)}\mathbf{w}^{(h)}. \tag{3}$$

To find an additive that satisfies the objective, we solve the following optimization problem:

$$\min_{\mathbf{w}^{(f)}} \|\mathbf{A}\mathbf{X}^{(f)}\mathbf{w}^{(f)} + \mathbf{A}\mathbf{X}^{(h)}\mathbf{w}^{(h)}\|_2^2 + \lambda J\left(\mathbf{w}^{(f)}\right) \quad \text{s. t. } \mathbf{w}^{(f)} \geq \mathbf{0} \tag{4}$$

where $J(\cdot)$ could be one of a number of possible regularization terms meant to promote secondary objectives such as monetary frugality, sparsity, or nutrition.

4. EXAMPLE

To demonstrate our approach to food steganography, in this section we design food additives to act as steganographic keys for cooked broccoli, where the cover medium may be cheese or mango juice.

The first step is to learn the structure-odor mapping matrix $\mathbf{A}$, as given in Section 2. The percept matrix $\mathbf{Y} \in \mathbb{R}^{146\times 143}$ that is used is from the Atlas of Odor Character Profiles [10], which has characterized 143 compounds such as citral, coumarin, and hexyl cinnamic aldehyde in terms of 146 odor descriptions like crushed grass, soapy, and burnt rubber using pooled data from a panel of hundreds of flavor/fragrance experts. We obtained physicochemical data for these same compounds to build the matrix $\mathbf{X} \in \mathbb{R}^{18\times 143}$ using PubChem,[1] performing matching and joining using Chemical Abstracts Service (CAS) Registry numbers. The 18 physicochemical descriptors include: topological polar surface area (TPSA), hydrogen bond acceptor count, partition coefficient prediction (XLogP), molecular weight, complexity, atom chiral count, rotatable bond count, and heavy atom count. Note that several of these physicochemical attributes of compounds have been indicated to determine the hedonic percept called pleasantness [13, 16, 17]. Solving (1) with this data and $\lambda = 1$, the rank of the learned mapping is 16.

With $\mathbf{A}$ in hand, the next step is to characterize the averse food, broccoli, both physicochemically and perceptually. First we determine the 21 flavor compounds in cooked broccoli, given in Table 1, from the Volatile Compounds in Food (VCF) database.[2]

[1] http://pubchem.ncbi.nlm.nih.gov
[2] http://www.vcf-online.nl

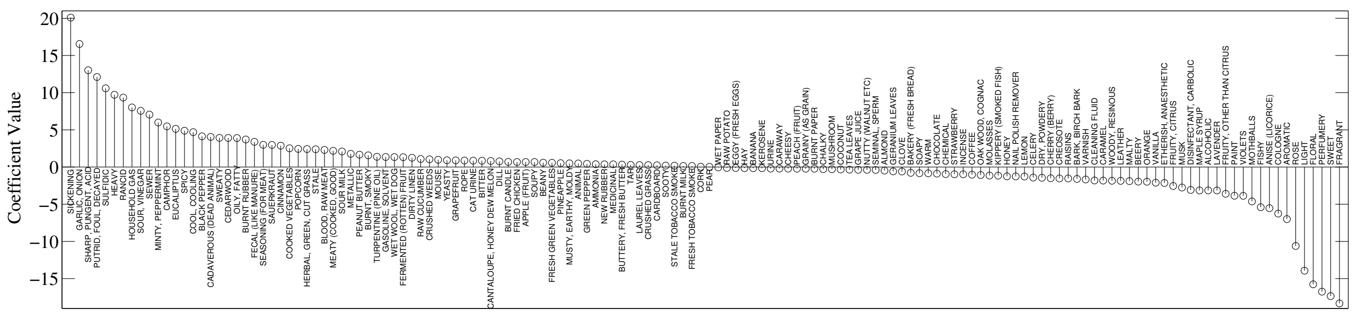


Fig. 2. Perceptual projection of the mixture of compounds contained in broccoli.

Conc.	Compound Name
0.0065	benzaldehyde
0.0324	1-octanol
0.0162	4-methylacetophenone
0.0811	phenylacetaldehyde (=benzeneacetaldehyde)
0.2596	nonanal (=pelargonaldehyde)
0.0162	limonene
0.0973	phenethyl isothiocyanate
0.0162	(E,E)-2,4-decadienal
0.0649	dimethyl trisulfide (=2,3,4-trithiapentane, methyltrithiomethane)
0.0162	2-pentylfuran
0.0162	2,3,5-trithiahexane
0.0162	(E,Z)-2,4-heptadienal
0.0973	(E,E)-2,4-heptadienal
0.4867	4-(methylthio)butyl isothiocyanate
0.0162	2-hexenal
0.6489	5-(methylthio)pentanenitrile
0.0162	dimethyl disulfide (=methyldithiomethane)
0.4867	3-phenylpropanenitrile (=phenethyl cyanide, benzenepropanenitrile)
0.0227	1,2-dimethoxybenzene (=veratrole)
0.0649	(Z)-3-hexen-1-ol (=leaf alcohol)
0.0162	benzothiazole

Table 1. Olfactory compounds in cooked broccoli with their concentrations.

Conc.	Compound
10.4520	methane
5.6617	2,5-hexanedione (=acetonylacetone)
4.6890	cyclotetracosane
3.1862	cubenene
1.7275	1,1'-dioxybis(1-decanol)
0.6456	2,4-diphenylpyrrole
0.5931	propanamide
0.5685	cyclooctatetraene
0.5044	heptatriacontene (unkn.str.)
0.3386	p-1,5-menthadien-7-ol
0.3376	2-ethyl-5-pentanoylthiophene
0.1209	ethylpyrrole (unkn.str.)
0.1106	docosahexaenoic acid (unkn.str.)
0.0224	10-methyl-2-undecenal
0.0055	α-maaliene
0.0041	2-(2-methylbutanoyl)furan

Table 2. Additive mixture composed of pure compounds for food steganography with cooked broccoli as the hidden data.

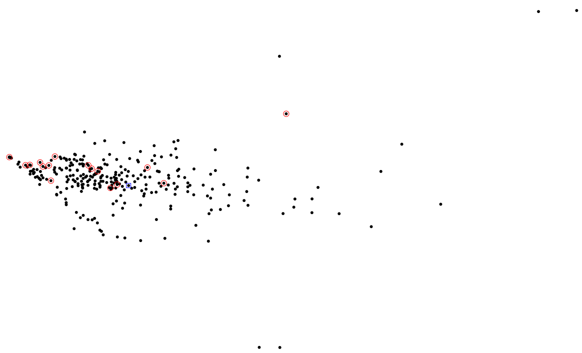
Due to data availability considerations, we take the concentration values alone as the weights w_j and normalize to unit ℓ_2 norm, obtaining the physicochemical representation of the mixture $\mathbf{X}^{(h)}\mathbf{w}^{(h)}$. If we project the mixture into perceptual space using $\mathbf{A}^*$, the result is shown in Fig. 2. The most prominent odor descriptors are sickening, garlic/onion, and sharp/pungent/acid.

Now we solve the inverse problem (4) to find food additives required to be the steganographic key for broccoli with two different dictionaries $\mathbf{X}^{(f)}$. One dictionary is 5736 pure compounds whereas the other dictionary is 297 food products in VCF. We only include food products with at least 15% of their listed compounds having both a match in PubChem and having a concentration value listed. If a range of concentrations is listed in VCF we use the midpoint of the range; if the value is listed as 'trace,' we use the value 10^{-6} parts per million. All food ingredient concentrations are normalized to have unit ℓ_2 norms. The result based on the pure compound dictionary is shown in Table 2 and the result based on the food ingredient dictionary is shown in Table 3. Angelica seeds which have a very unique pleasant smell unlike anything else, are the main component of the food product-based additive.

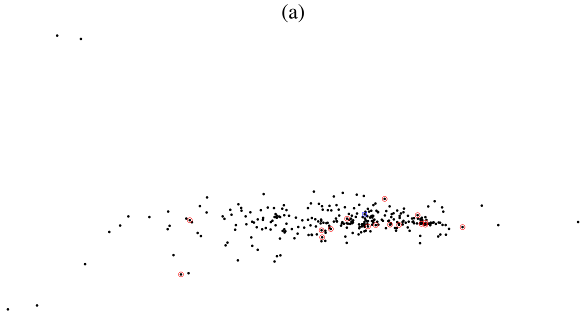
We can also view the food ingredients-based additive in physic-

Conc.	Food Product Name
13.2999	ANGELICA SEED OIL
7.5619	CUMIN SEED (Cuminum cyminum L.)
7.5328	MUSSEL
4.3985	BARLEY (unprocessed)
2.8275	LOBSTER
2.7808	BLACKBERRY BRANDY
2.5717	ROSE WINE
2.3048	OTHER VITIS SPECIES
1.4727	TURNIP
1.3033	LAMB and MUTTON FAT (heated)
0.8432	INDIAN DILL ROOT (Anethum sowa Roxb.)
0.6520	LOGANBERRY (Rubus ursinus var. loganobaccus)
0.4794	ELDERBERRY FRUIT
0.1626	PEANUT (raw)
0.0989	MICROCITRUS SPECIES OIL
0.0285	PRAWN

Table 3. Additive mixture composed of food ingredients for food steganography with cooked broccoli as the hidden data.



(a)



(b)

Fig. 3. First two principal components of the (a) physicochemical space and (b) perceptual space of the food ingredients dictionary. Broccoli is enclosed by a blue square and the components of the additive mixture are enclosed by red circles.

ochemical and perceptual spaces; Fig. 3 depicts the spaces through principal components projections. The additive and broccoli together provide a good span of the spaces, which is a property of flavor whiteness. Broccoli plus its specific additive appears to be white.

5. CONCLUSION

Human food aversion and food intake behavior can have significant consequence for health, well-being, and happiness. Hence if there is a way to hide one food inside another, it can be quite powerful.

In this paper, we have cast such food hiding as a problem of steganography and developed olfactory signal processing techniques to design optimal additives to enable this process. Carrying out the design procedure required putting together data on the flavor composition of ingredients (from gas chromatography–mass spectrometry), the molecular properties of flavor compounds (from chemoinformatics), and the human perception of flavors (from hedonic psychophysics) with algorithmic techniques for function learning and inverse problem solution.

Moreover this paper demonstrates that with emerging understanding of the neural and chemical basis for human olfaction, it is possible to extend statistical signal processing methodology to this new multimedia domain.

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