Compressive Spectrometer

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***Abstract*—Spectrometers are widely used for characterizing materials. Recently, filter-based spectrometers have been proposed to lower the manufacturing cost by replacing optical components with low-cost wavelength-selective filters, but at the expense of possibly lowered signal quality. We present compressive spectrometers which, based on the compressive sensing principle, are able to recover signal with improved quality from measurements acquired by a relatively small number of low-cost filters. We achieve high quality recovery by leveraging the fact that spectrometer measurements typically follow the shape of a smooth curve with a few spikes. We validate our method with real-world measurements, and release our dataset to facilitate future research.**

I. Introduction

Spectral analysis is a well-established technique used in physics, chemistry, and biology. It provides detailed information related to the chemical bonds of the molecule, and thus can identify the compositions of the sample and their concentrations [1] [2].

Conventional optics-based spectrometers are expensive due to high-cost optics components and their large physical footprints. Recently, miniature filter-based spectrometers [3] [4] have emerged to provide cost and size advantages over optics-based spectrometers. Instead of using dispersers, the new approach employs a bank of wavelength-selective filters to detect the corresponding spectrum. However, these miniature spectrometers usually cannot resolve the spectrum at a fine-gain level due to the difficulty of manufacturing filters with small leaks, resulting in lower signal quality. Additionally, many filters are needed in order to capture a large set of target wavelengths.

To overcome the drawbacks of filter-based methods [5], our proposed compressive spectrometers use a small number of filters to capture information from multiple wavelengths at the same time. Based on sparse signal recovery principles in compressive sensing [6], we present a high-quality signal reconstruction method that exploits the fact that spectrum signal normally exhibits itself as a smooth curve with a few spikes.

II. Hybrid Model of Smoothness and Sparsity

Spectrum signal tend to be a smooth curve with a few spikes of varying magnitudes. This is the result of several contributing factors throughout the sensing process, as illustrated in Figure 1. We propose a signal model that treats the signal x as the composition of a sparse component and a smooth one: $x = v + \Psi z$ where v is smooth, Ψ is a sparsifying basis and z is sparse. The measurements y is defined as $y = \Phi x$ where Φ is the sensing matrix.

The sparsity and smoothness assumption manifests as separate regularization terms in the optimization problem for signal reconstruction:

$$\arg\min_{v,z} \|y - \Phi(v + \Psi z)\|_2^2 + \lambda_1 \|z\|_1 + \lambda_2 \|Av\|_2^2 \quad (1)$$

where A is a bidiagonal (1, -1) matrix such that Av captures gradients in adjacent components of v. The choice of using ℓ_2 norm rather than ℓ_1 norm for Av reflects the fact that v is more likely to have many small changes instead of few large ones. Note that (1) is convex and can be solved efficiently with gradient descent methods [7].

III. Evaluation

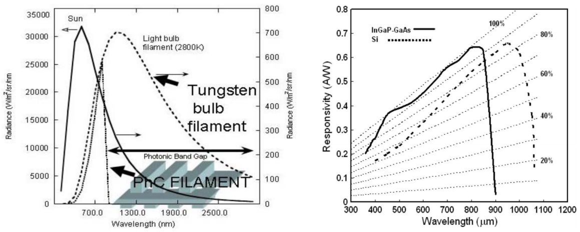
To evaluate our method, we collected a dataset [8] that includes compressive spectrometer characteristics (see Figure 4) and spectrum of common plastic objects in the real world (see Table I). Note that our dataset is much more realistic compared to signals used in prior spectrometer signal recovery experiments, which only focused on simple Gaussian-like responses from simple LED sources.

We compare our hybrid method with state-of-the-art methods: conventional sparsity-based recovery method using a sparse model in l_1 [3] and the Tikhonov regularization method in l_2 (based on smoothness assumption) [4]. As shown in Table II, our method achieves significant better performance in minimizing recovery error than the state-of-the-artmethods for our dataset. We consider the signal reconstruction error as a function of the number of filters (i.e., number of measurements) used, where the sensing matrix Φ is drawn from Gaussian distribution. As shown in Figure 2, our hybrid method consistently delivers superior reconstruction quality.

IV. Conclusion

We propose compressive spectrometers that can have lower manufacturing cost. This is because unlike conventional filter-based spectrometers, our method does not require filters with small leakage, and uses much fewer filters for signal reconstruction.

Our method leverages the fact that spectrum signals tend to exhibit a few spikes over a smooth curve. By enforcing sparsity (for spikes) and smoothness in the signal recovery process, we achieve low reconstruction error even under significant compression (Figure 2). We validate our method with real measurements from spectrometers, and release our dataset to the community to facilitate research.



(a) (b)

Fig. 1. Several factors contribute to the final spectrum detected by a spectrometer. First, the light source is smooth and relatively broadband as shown in (a) [9]. This source signal reflects off some surface that selectively absorbs certain specific narrow bands depending on the surface material properties. Then, the reflected signal is captured by the sensor with characteristics as shown in (b) [10]. As a result, the signal acquired at the sensor would be roughly smooth except around the narrowband wavelength segments absorbed by the reflective surface.

TABLE I
NUMBER OF SAMPLES FROM EACH PLASTIC TYPE IN THE DATASET.

	No.1	No.2	No.3	No.4	No.5	No.6	No.7	Total
(A)	10	13	7	11	11	11	2	65
(B)	20	20	20	20	40	20	20	160

Our spectrum signals are collected using a RED-Wave-NIRX-SR spectrometer with SL1 tungsten lamp. In setting (A), we measure several spectrum from different items within the same plastic type. This captures the inter and intra-class variations of different plastic types. In setting (B), for each plastic type we measure several spectrum of the same item with varying distance, location, angle, etc. This captures the variations in measuring the same material.

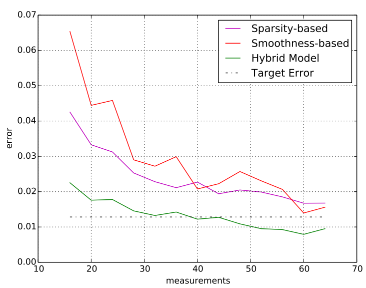


Fig. 2. Performance of different methods over number of measurements. The parameters for each method are screened over different numbers of measurements. Our proposed hybrid method outperforms methods that only rely on either sparsity or smoothness. The dotted line shows the target error for material classification.

TABLE II
COMPARISON OF RECONSTRUCTION ERROR USING REAL FILTERS

	SC [3]	TV [4]	Hybrid	Target
Error	.021	.038	**.013**	.013

This table shows recovery error using Φ measured from a real spectrometer. Due to the manufacturing process, the actual filters tend to be very smooth and Φ is in fact quite coherent as shown in Figure 4. This specific spectrometer has 64 filters, which correspond to 64 measurements. As a reference point, we define the normalized variance between samples from the same object as the target error.

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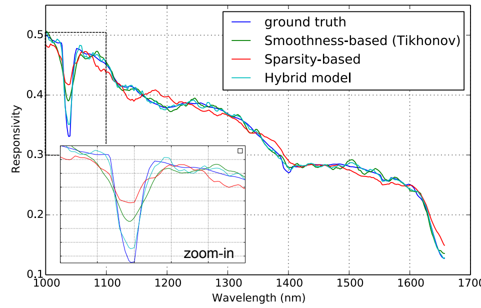

Fig. 3. Reconstructed signals under different methods (plastic type II). The hybrid model is able to capture the valley more accurately (see the inset).

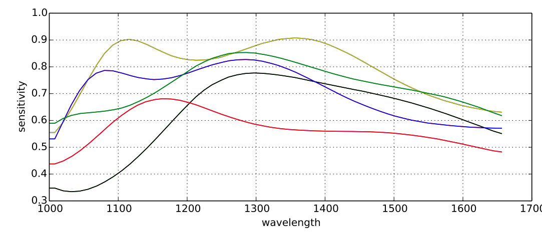

Fig. 4. Examples of filter responses from a compressive spectrometer. The filter characteristics matrix Φ (i.e., the sensing matrix) is measured using the Oriel Cornerstone 130 monochromator at the wavelength interval between 1000nm and 1656nm. The signal resolution of the monochromator is 12nm. We upsampled it to match the resolution of the ground-truth signals at 1nm.

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