COMPREHENSIVE COMPUTATIONAL SPECTRAL DATA COLLECTION SYSTEMS: A REVIEW

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Abstract

As computer science advances, an increasing number of hardware implementations may be mimicked by software programming, bringing small, inexpensive, and quick components to image apparatus. Recent years have seen the introduction of computer techniques for spectral detection and the emergence of computational spectrum acquisition systems. In contrast to conventional non-computational approaches, this research emphasizes the benefits of computational spectrum acquisition implementations. Then, with an emphasis on the compact characteristic, we examine the implementations that are the most representative before concluding with a discussion and a prognosis.

***Key words**: Spectral imaging; Computational imaging; Spectrometer*

Introduction

The history of spectral detection is extensive. Isaac Newton created the first spectral detection in 1665 (Newton, 1979), dividing sunlight into a rainbow-colored pattern using a triangular prism. However, it wasn't until Kirchhoff and Bunsen (1861) constructed the first useful spectrometer that it was able to analyze the spectrum quantitatively. The direct reading spectrometer was created in the 1960s when semiconductor and photoelectronic technology advanced, making it easier to store and analyse spectral data. Since the 1980s, when two-dimensional (2D) charge coupled device (CCD) arrays first appeared, advances in optical design, electronics, and manufacturing have all helped to significantly improve performance, ushering in a prosperous new era for spectrum acquisition instruments. Since then, spectral imaging technology has been frequently used (Hagen and Kudenov, 2013). However, there are still a number of drawbacks with traditional spectrometer and spectrum imaging equipment, including their high cost, large volume, and heavy weight.

With the advancement of computer science in recent years, an increasing number of hardware implementations may now be replicated via software programming, bringing small, inexpensive, and quick components to image instruments. The initial drawbacks of spectral detection and computational reconstruction procedures are anticipated to be overcome as a result of the introduction of several computational methodologies. A inexpensive, lightweight, and compact spectrum collection device may also be widely used, lowering the bar for consumers to detect spectrum. Even on smartphone platforms, portable sensing devices are already feasible (Das et al., 2016).

In recent years, several types of computational spectral detection techniques have been created. There are some hazy broad guidelines for determining if an approach is computational. First, in order to get modified spectrum data, computational spectral detection methods often employ spectral modulating or under sampling components. In order to extract spectral information from raw data, complex algorithms are used. However, some non-computational approaches use some degree of computing, such as data mapping, super-resolution techniques, and de-noising algorithms. It is crucial to define computational techniques precisely before trying to compare computational approaches for spectral detection.

Only approaches whose raw data may be comprehended by applying a computational transform to it are the focus of this study. In all honesty, the software's output data does not resemble the raw data that the hardware of the system gathered. This separates computational implementations from conventional spectrum information acquisition systems by making computation the system's core functionality.

We discuss many computational spectrometers and computational spectrum imaging systems in this article. Although the physics behind conventional spectrometers and spectrum imaging systems vary, the concepts are similar in computing implementations, which is why they are seldom compared side by side. As a result, we consider both systems to be systems for computing spectral information acquisition.

Grating-based coded aperture spectrometer

According to Wolffen- buttel (2004), a classic grating-based spectrometer is made up of five components: a slit entry, collimating optics, a dispersive element (often a grating), focusing optics, and a detector array. The hardware device samples a slit portion of a test light source and creates a spanned spectrum distribution on a detector array plane based on the dispersive characteristic of the grating element. Thus, the intensity distribution of scattered light is measured in order to determine the shape of the spectrum. Slit-based dispersion spectrometers have a significant trade-off in spectral resolution and light throughput, however. A longer slit and detector are needed to increase light throughput in a slit spectrometer while preserving the spectrum resolution, which increases the system's size and cost (Cull et al., 2007).

A static multi-modal and multiplex spectrometer (static MMS) is a 2D coded aperture technique that Gehm et al. (2006) introduced and improved for the spectral characterization of diffuse sources. Mathematically, Gehm et al. (2006) demonstrated that the orthogonality criterion must be satisfied via 2D coding. The input aperture pattern might be based on any family of orthogonal func- tions to satisfy the design requirement. Notably, since Parseval's relation does not hold, the noise level naturally rises when the continuous mask codes (harmonic and Le-gendre basis) are used. The discrete codes are favoured as a result. The device simultaneously boosted light throughput and signal-to-noise ratio (SNR) without losing spectral precision by swapping out the slit for an orthogonal column code based on a row-doubled Hadamard matrix. Fig. 3 displays the intensity picture that has been distortion-corrected and was obtained using the coded aperture approach. The output of static MMS is increased by roughly 10 times compared to a slit spectrometer, and the SNR is increased by around 3.4 times.

By switching the monochromatic CCD detector array for a color one and the dispersive element for a holographic grating, Gehm et al. (2007) increased the static MMS (Cull et al., 2007). With three distinct spectral bands and a center wavelength that corresponds to blue, green, and red light, the holographic grating was created. As opposed to previous multiplexing spectrometer designs, which separate spectral bands along the non-dispersing axis, this one's grating periods are designed to disperse each band's entire spectral range over the detector. Consequently, the method was known as dispersion multiplexing.

With permission from OSA spectrometer (DMS), Gehm et al. (2006), Copyright 2006, have been reprinted. Three spectral bands end up incident on the same detector pixels as a consequence of them. In order to detect the spectrum, color CCD was used. The overlapping bands may be distinguished by recreating data from each color channel independently. A non-negative least-squares approach was used to calibrate the data shifting caused by the spectral response difference between holographic grating and CCD Bayer filters (Cull et al., 2007). A comparison between the final detected spectrum and the spectrum produced by an Ocean Optics USB 2000 spectrometer was made (Fig. 4). It is important to note that the peak positions are discernible. The coded aperture was converted into a 37-ordered modified uniformly redundant array (MURA) shortly after DMS by Feller et al. (2007) (the same team as Gehm), who called the system "multi-order coded aperture" (MOCA). A neon pen lamp's spectrum detection result was compared to that of an Ocean Optics USB 2000 spectrometer (Fig. 5).

The coded aperture spectrometer can measure a larger total spectral range with a tiny detector thanks to multiplexing and computational reconstruction techniques, which facilitates shrinking. In reality, the DMS has a form that is about the size of a key and measures about a centimeter (Fig. 6).

Filter-based computational spectrometer

With a few minor exceptions, the fundamental design of a filter-based spectrometer is substantially the same as a grating-based spectrometer. Three components—light collecting lenses, filters, and detector(s)—make up the majority of the hardware.

The optical properties of incoming light, such as incidence angle, flux, and stray light level, are more appropriate for filtering and detection. Reprinted from Cull et al. (2007), Copyright 2007, with permission from OSA. Different wavelength components are separated sequentially or spatially as the light passes through the filters. Finally, the detector or detector array measures each component, allowing the system to gather the spectral data of the test sample.

The filter is the key distinction between conventional and computational spectrometers. In the past, bandpass filters have been used to do wavelength decomposition tasks. The employment of additional filters with smaller passbands results in increased spectral resolution. The system as a whole becomes more complicated and volumetric as a result of this method. In the meanwhile, light throughput decreases as the spectral response curve becomes narrow, leading to a reduced SNR. Broadband filters are used in computational applications, rendering the raw data completely different from the original spectrum. However, spectral resolution may be addressed by using computational reconstruction procedures. Broadband filters enable the detection of the spectrum from a darkened scene because they let much more light to pass through. Further, using sensing filters that are properly designed, the compressive sensing theory predicts that it is possible to recover a sparse spectrum with a high probability while using fewer filters than the desired spectrum channels (recovering a higher-dimensional vector from a lower-dimensional vector), which is unquestionably a good approach for miniaturization. However, by employing regularization techniques to de-noise a higher-dimensional vector from a lower-dimensional vector, noise may be minimized using a bigger filter number, which improves the SNR and strengthens the whole system.

Low-cost thin-film spectrometer

Chang and Lee (2008) demonstrated how a fine spectrometer on a chip based on a subpar and inexpensive filter array is feasible. The fundamental system model of the spectrometer based on a static filter array is shown in Fig. 7. An array of photoelectric sensors, such as CCD sensors, are put immediately on top of an array of filters. A CCD sensor or a collection of CCD sensors may represent a filter. A digital signal processor is then given the outputs from the CCD sensors (Chang and Lee, 2008). Its hardware system topology resembles that of a typical filter-based spectrum analyzer; the filter array's spectral distribution curve is its sole distinctive component. All filters are broadband, so-called low-cost filters, as illustrated in Fig. 8. The prototype system uses a non-negative constrained least-squares (NNLS) method to reconstruct the spectrum data, and the filter number is 40. We can only draw the conclusion that the prototype system can locate the center wavelength of a Gaussian-shaped spectrum at about 2 nm error level because Chang and Lee (2008) only displayed the reconstruction results of a narrow-band Gaussian-shaped spectrum. Further quantitative evaluation, however, is not possible.

Chang et al.'s (2011b) software implementation was upgraded, and they produced a complex study of reconstruction accuracy. The reconstruction strategy for noise reduction employed a Gaussian kernel template, and the algorithm was enhanced into a l1-norm minimization technique. In both simulation and actual measurements, comparisons were done between NNLS, Tikhonov regularized non-negative least squares (TNNLS), and the l1-norm method. The measurement included a broadband sample (tungsten halogen light filtered via colored plastic). Achieving a mean absolute error of less than 1 nm for full width at half maximum (FWHM) and less than 0.5 nm for center wavelength, Chang et al. (2011a) increased the filter number to 119 and used the system to accurately measure light emitting diode (LED) spectra. The experiment demonstrated the feasibility of employing a low-cost sensor device to match the functionality of an optical spectrometer of laboratory grade. It is important to note that since the system can only support a single LED of the same kind, the measurement accuracy level cannot accurately reflect the spectrum resolution. Application possibilities are constrained by the measurement result's strong dependence on previous stages of training and the choice of the Gaussian basis number.

Oliver et al. (2012) (the same group as

Chang) took use of a signal spectrum's sparseness to demonstrate how resolution may be increased over the limit imposed by the number of filters. Oliver et al. (2013) reconfigured the filters into a collection of random transmittances, mirroring some of the studies in compressive sensing (CS) (Candès et al., 2006; Donoho, 2006; Baraniuk, 2007; Candès and Wakin, 2008) with respect to the usage of random matrices for signal capture and recovery. When the spectrum channel number N increased to 405, 40 filters were used to keep the reconstruction mean square error (MSE) within 5 dB. Additionally, by redesigning the filter, the resolution can be shown from 6.5 to 0.99 nm.

The resolution, it should be noted, was generated from an MSE-based definition, which accurately reflects the genie-aided MSE level of sparse signal reconstruction (Oliver et al., 2013). In other words, rather than a random natural spectrum, this resolution result only matches certain spectrum measurements. The random thin-film filter (TF) design, on the other hand, exhibits a 7-fold resolution gain over low-cost TFs, which is advantageous for spectrometer shrinking.

Etalon-based spectrometer

Etalons possess the spectrum filtering property broadly speaking. The Fabry-Perrot etalon-based spectrometer is regarded as a specific kind of filter-based spectrometer in this instance. The etalon may be categorized as a generalized broadband filter since it has a wavelength selectivity of various wavelengths. A computational spectrometer is a spectrometer that makes advantage of the etalons' large spectral range.

In further detail, the optical spacing layer is a 700 nm SiO2 layer beneath a 1010 PMMA step-structure with a thickness range of 0.8-2.8 m, for a total cavity thickness variation of 1.5-3.5 m in 100 steps (Huang et al., 2017). The semi-reflecting surfaces are 30-nm silver films (reflection is around 0.7). The CCD sensor was positioned atop the cavity array. The etalons' fineness and thickness range influence the resolution that may be achieved. According to the Nyquist sampling principle, the EARS system delivers an equal spectral resolution of 8 nm at a sample period of 4 nm. However, by using the nature of compressive sensing, the resolution might surpass the resolution limit if the signal is known to be sparse on a specific basis. The wavelength center positioning precision, for instance, may be as high as 0.12 nm if the signal is recognized as coming from a laser source.

2.2.3 New material filter spectrometer

More degrees of freedom for manipulating physical variables are made available by advances in material science and nanotechnology, and spectrum modulation yields numerous novel results. The limits of conventional production are partially addressed by new material-based techniques, expanding the range of spectral detection. Here, we provide a quick overview of a number of exemplary novel material-based filter spectrometer implementations.

Quantum dot spectrometer

A broadband spectrometer based on quantum dot filters was presented by Bao and Bawendi in 2015. The 2D absorptive filter array, made up of 195 colloidal quantum dots (CQDs), takes the place of interferometric optics in the tiny spectrometer, which achieves a spectral resolution of 1 nm with a measuring range of 300 nm. The quantum dot spectrometer and broadband filter spectrometer share all benefits as a result of their identical fundamental structures. By expanding the variety of CQDs employed in the filter array, it is possible to simultaneously improve the spectrum channel number and spectral range without reducing overall photon efficiency.

PC slabs may be made using single exposure photolithography with just common CMOS components. The technique may be extended to any wavelength range by scaling the size of the PC since the spectral response functions are entirely extrinsic and enabled by structures rather than material features, providing this implementation a significant promise for the downsized spectrometer.

Computational spectral imaging

In contrast to spectrometers, spectral imaging collects a 3D data cube that includes both spectral () and spatial (x, y) data. Spectral data is better understandable with a spatial resolution. Consequently, it is simple to get the spatial distribution of spectral information. In certain applications, including geological survey and agricultural disease evaluation, spatial distribution data may be more significant than a high spectral resolution. The simultaneous collection of spatial and spectral data, which increases system complexity, makes it more difficult to gather 3D information since spatial and spectral data are typically collected using separate procedures. Traditional spectrum imaging techniques utilize either time division or space division to multiplex the spatial and spectral dimensions, which results in trade-offs between spectral and spatial resolutions (or frame rate).

Computational techniques may be used to overcome the aforementioned issues. The emergence of compressive sensing theory allows for the extremely compressed storage of recorded data. Here, we divide computational spectral imaging techniques into two categories: compression of data during computation in the spectrum () dimension and calculation of data during computation in the spatial (x, y) dimension. This section focuses on spectrum imaging implementations that use computational techniques to create portable, all-around systems.

Computation in spectral (λ) dimension

Directly using a spectrometer to collect the spectrum of each pixel and then combining the data to create a spectral picture is the simplest technique to convert spectrometry into a spectral imaging device. The spatial resolution or frame rate of spectrum detection may be greatly enhanced by utilizing computational approaches to compress the spatial or temporal effort. In fact, any spectrometer-based imaging technique described in Section 2 may be seen as computational spectral imaging, which involves doing computations in the spectrum dimension. There are few efforts at spectral imaging, and computational spectrometers are often created from scratch.

Computed tomography imaging spectrometry

The computerized tomography imaging spectrometry (CTIS) is a common computational method. Bulygin and Vishnyakov (1992) and Oka-moto and Yamaguchi (1991) each separately developed this idea. Ford et al. (2001) created the first high-resolution CTIS after years of research and development. The spectral channel number was 55 and the spatial resolution was 203x203 pixels using a 2048x2048 CCD camera. By using a 2D dispersion element, CTIS systems (Fig. 20) vary the mixing of spatial and spectral data at various points on the detector. The tomographic methods can recreate the spectral picture after the aliasing compresses the spectral and spatial data into a single shot. The system configuration is made more compact in this manner.

2. HyperCam

"HyperCam" is a product created by Goel et al. (2015) for widespread spectrum imaging. It features a straightforward system design, consisting of a 17-LED light source, a driver board, and a CMOS camera (Goel et al. (2015) provide a photo of the system). Each component is affordable and designed for everyday usage. The spatial resolution is 12801024, and the frame rate ranges from 9 to 150 frames/s depending on the number of channels employed.

To span the camera sensitivity range, narrowband LEDs were experimentally chosen. Goel et al. (2015) have the spectrum power distribution curves of LEDs accessible. The spectral resolution is not anticipated to be good since these spectral curves are considered to be poor circumstances in classical spectral detection. Goel et al. (2015) improved the system in an application-oriented manner as opposed to focusing on spectrum reconstruction accuracy. For two distinct applications—namely, user-specific feature acquisition in a multi-user interaction system and food monitoring—a great deal of software computational work has been done.

The multi-channel picture was initially captured, and it was then calculated to create an immersed image that highlights the hand feature. The assessment shows that this method reliably distinguishes between five users at once, which is appropriate for the majority of multi-touch surface systems. The system accurately predicted relative ripeness in the second application, which is more widely used, with an accuracy of 94% (as opposed to an accuracy of 62% when utilizing RGB pictures) (Goel et al., 2015).

The HyperCam architecture demonstrates the potential for widespread spectrum imaging. Although the spectral performance of such devices is not encouraging, we think that with the advancement of hardware design and machine learning algorithms, affordable spectrum imaging devices may become extensively employed in particular recognition applications.

Computation in spatial (x, y) dimension

A novel imaging method has been created to acquire an image with compressed sampling in response to the introduction of the single pixel imaging idea (Takhar et al., 2006; Duarte et al., 2008) derived from compressive sensing (Candès et al., 2006; Donoho, 2006; Baraniuk, 2007; Candès and Wakin, 2008). An l1-norm minimization approach may be used to rebuild the picture from a single pixel detector using a spatial light modulator (SLM) to provide variable spatial coding. Additionally, if the scene is somewhat "sparse," the captured data may be greatly reduced, which is advantageous for spectrum imaging. Under this configuration, a spectral picture may be captured using a spectrometer as a single pixel detector. Over the last ten years, attempts have been undertaken.

Conclusions

Over the last several decades, spectral information collecting technology has advanced quickly. Numerous novel implementations have surfaced as a result of the use of new materials and computer algorithms, opening up new possibilities for spectrometers and spectrum imaging.

The majority of computational spectroscopy equipment may still operate with lower precision than conventional equipment. However, this flaw becomes less significant when seen through the lens of ubiquitous applications, such smartphone-based detection or spectrum-based identification. Instead, the advantages of these technologies are their affordable, lightweight, and small enclosures. These benefits are almost usually more alluring than aiming for perfection in such applications. Consumer-friendly spectral detection has recently received some attention. We believe that widespread spectral information use will result from the co-design of hardware and computational algorithms, and that as the Internet of Things (IoT) and artificial intelligence (AI) develop, ubiquitous spectrometers and spectral imaging will benefit humankind.

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