SPIE. DEFENSE+ COMMERCIAL SENSING

CONNECTING MINDS.
ADVANCING LIGHT.

CURRENT AS OF 12/2015

CHECK ONLINE FOR UPDATES

2016 SPIE DEFENSE + COMMERCIAL SENSING.

ADVANCE TECHNICAL PROGRAM

www.spie.org/DCS16PROGRAM

ATTEND

APRIL • 2016

Baltimore Convention Center
Baltimore, Maryland, USA

Conferences & Courses
17–21 April 2016

EXPO
19–21 April 2016

The Leading Global Event for Sensing, Imaging, and Photonics Technologies

DEFENSE + SECURITY

COMMERCIAL + SCIENTIFIC SENSING AND IMAGING

DEFENSE + COMMERCIAL SENSING EXPO

TUESDAY 19 APRIL

SESSION 4 . . . . TUE 8:20 AM TO 10:50 AM

Novel Spectrometers and Applications II

Session Chairs: **Mark A. Druy** (USA);
Ellen V. Miseo, Hamamatsu Corp. (USA)

Silicon based large area filters: A path way to high resolution, low cost adaptive focal plane arrays *(Invited Paper)*, Dhirendra Kumar Tripathi, K. K. M. B. Dilusha Silva, Jorge Rafel Silva Castillo, Jarek Antoszewski, Mariusz Martyniuk, Lorenzo Faraone, The Univ. of Western Australia (Australia). . . . . [9855-17]

Issues concerning short-wave infrared signature reduction of dyed fabrics, Scott A. Ramsey, Daniel C. Aiken, Troy Mayo, Samuel G. Lambrakos, Joseph E. Peak, U.S. Naval Research Lab. (USA) . . . . [9855-18]

On-chip spectrometer based on an evanescently coupled multimode spiral waveguide, Brandon Redding, Seng Fatt Liew, Raktim Sarma, Yaron Bromberg, Hui Cao, Yale Univ. (USA). . . . . [9855-19]

Low cost long wave infrared spectrometer based on guided mode resonant effect, Mark Mirotznik, Univ. of Delaware (USA); Neelam Gupta, U.S. Army Research Lab. (USA); Victoria Carey, Morgan McElhiney, Univ. of Delaware (USA) . . . . [9855-20]

Handheld and mobile hyperspectral imaging sensors for wide-area standoff detection of explosives and chemical warfare agents, Nathaniel R. Gomer, Matthew P. Nelson, Charles W. Gardner, Patrick J. Treado, ChemImage Corp. (USA). . . . . [9855-21]

A novel CMOS-compatible, monolithically integrated line-scan hyperspectral imager covering the VIS-NIR range, Klaas Tack, Pilar Gonzalez, Bert Geelen, Bart Masschelein, Charle Wouter, Bart Vereecke, Andy Lambrechts, IMEC (Belgium) . . . . [9855-22]

The use of FTIR for the detection of chemical warfare agents and toxic industrial chemicals, Larry McDermott, MKS Instruments (USA); Timothy Stickler, KD Analytical (USA); Sylvie Bosch-Charpenay, Oskar Bosch, Norm Smith, MKS Instruments (USA) . . . . [9855-23]

Pub Crawl in the Exhibit Hall

Tuesday, 19 April 4:30 to 6:00 pm
Location: Exhibition Hall

Enjoy free drinks and appetizers while learning about products and services offered by top companies in the industry.

TUESDAY POSTER SESSION . . . . TUE 6:00 PM TO 7:30 PM

Interactive Poster Session

All symposium attendees – You are invited to attend the evening Interactive Poster Session to view the high-quality posters and engage the authors in discussion. Enjoy light refreshments while networking with colleagues in your field. Authors may set up their posters between 7:30 am and 5:00 pm the day of their poster session. Special daytime previewing prior to the session from 10:00 am to 5:00 pm. Attendees are required to wear their conference registration badges to access Level 200, Mezzanine to view the posters.

Posters that are not set up by the 5:00 pm cut-off time will be considered no-shows, and their manuscripts may not be published. Poster authors should accompany their posters from 6:00 to 7:30 pm to answer questions from attendees. All posters and other materials must be removed no later than 8:00 pm. Any posters or materials left behind at the close of the poster session will be considered unwanted and will be discarded. SPIE assumes no responsibility for posters left up after the end of each poster session.

Optical unmixing using programmable spectral source based on DMD, Ding Luo, Fraunhofer-Institut für Optronik, Systemtechnik und Bildauswertung (Germany) and Karlsruher Institut für Technologie (Germany); Sebastian Bauer, Karlsruher Institut für Technologie (Germany); Miro Taphanel, Thomas Längle, Fraunhofer-Institut für Optronik, Systemtechnik und Bildauswertung (Germany) and Karlsruher Institut für Technologie (Germany); Jürgen Beyerer, Karlsruher Institut für Technologie (Germany) and Fraunhofer-Institut für Optronik, Systemtechnik und Bildauswertung (Germany) . . . . [9855-24]

Design of thin-film filters for resolution improvements in filter-array based spectrometers using DSP, Woong-Bi Lee, Gun Wu Ju, Yong Tak Lee, Heung-No Lee, Gwangju Institute of Science and Technology (Korea, Republic of) . . . . [9855-25]

Design of thin-film filters for resolution improvements in filter-array based spectrometers using DSP

Woong-Bi Lee, Cheolsun Kim, Gun Wu Ju, Yong Tak Lee, and Heung-No Lee*
School of Information and Communications, Gwangju Institute of Science and Technology, Republic of Korea, 61005

ABSTRACT

Miniature spectrometers have been widely developed in various academic and industrial applications such as bio-medical, chemical and environmental engineering. As a family of spectrometers, optical filter-array based spectrometers fabricated using CMOS or Nano technology provide miniaturization, superior portability and cost effectiveness. In filter-array based spectrometers, the resolution which represents the ability how closely resolve two neighboring spectra, depends on the number of filters and the characteristics of the transmission functions (TFs) of the filters. In practice, due to the small-size and low-cost fabrication, the number of filters is limited and the shape of the TF of each filter is non-ideal. As a development of modern digital signal processing (DSP), the spectrometers are equipped with DSP algorithms not only to alleviate distortions due to unexpected noise or interferences among filters but also reconstruct the original signal spectrum. For a high-resolution spectrum reconstruction by the DSP, the TFs of the filters need to be sufficiently uncorrelated with each other. In this paper, we present a design of optical thin-film filters which have the uncorrelated TFs. Each filter consists of multiple layers of high- and low-refractive index materials deposited on a substrate. The proposed design helps the DSP algorithm to improve resolution with a small number of filters. We demonstrate that a resolution of 5 nm within a range from 500 nm to 1100 nm can be achieved with only 64 filters.

Keywords: spectrometers, compressed sensing, sparse representation, resolution improvements

1. INTRODUCTION

Miniature spectrometers have been widely developed for various academic and industrial applications such as bio-medical, chemical and environmental engineering [1-2]. As a family of spectrometers, optical filter-array based spectrometers fabricated using CMOS or Nano technology provide miniaturization, superior portability and cost effectiveness [3]. As a development of modern DSP, the state-of-the-art filter-array based spectrometers are equipped with DSP algorithms not only to alleviate distortions due to unexpected noise or interferences among filters but also reconstruct the original signal spectrum [4-7]. In the filter-array based spectrometers, resolution which represents the ability how closely resolve two neighboring spectra, is determined by the number of filters and the properties of the TFs of these filters [5]. In practice, due to the small-size and low-cost fabrication, the number of filters is limited and the shape of the TF of each filter is non-ideal [5,7].

In order to improve the resolution beyond the fundamental limit determined by the number of filters, a L1 norm minimization based DSP algorithm was introduced in [5]. Furthermore, filters with random TFs were proposed in [6] and achieved 6 folds resolution improvements along with the DSP algorithm. In the random filter array, a TF of each filter is mutually uncorrelated with that of other filters as well as a transmission at one wavelength is completely different and uncorrelated with that at the other wavelengths in each filter. To implement the random filters, optical thin-film filters was proposed by randomly varying the thicknesses of the layers. Due to the limitations on the thicknesses of the layers and refractive indices of the materials of the layers, however, the TFs of the random filters in [6] are difficult to achieve in practical implementations.

In this paper, we propose a design of optical thin-film filters which have uncorrelated TFs. In consideration of real implementations, we determine SiO_2 and SiN_x for low- and high refractive index materials of the layers, respectively. The thicknesses of layers in each filter are limited to the order of hundreds of nanometers. Instead, the number of layers is increased for a large contrast between minimum and maximum of the TF. The spectrometer with the proposed filter-array and the DSP algorithms improves the resolution and the reconstruction performance.

*heungno@gist.ac.kr; phone 82 62 715-2237; fax 82 62 715-2204; infonet.gist.ac.kr

2. SYSTEM DESCRIPTION

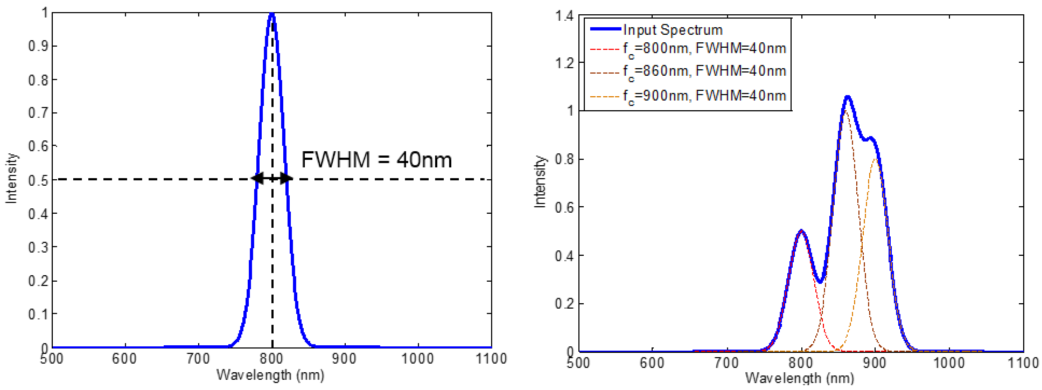
We consider a filter-array based miniature spectrometer. The filter-array consists of M filters. In each filter, multiple layers of materials with different refractive indices are alternatively deposited on a substrate [8]. According to the materials and thicknesses of layers, each filter has a specific TF, which represents the amount of light that the filter allows to be transmitted at a given wavelength λ. Let $f_i(\lambda)$ denotes the TF of i^{th} filter for $i = 1, 2, \cdots, M$. Each filter is attached to one or multiple CCD elements, and a set of a filter and its corresponding CCD elements forms a spectral detector. The output of the i^{th} spectral detector is then given by $y_i = \int_a^b f_i(\lambda) x(\lambda) d\lambda + n_i$, where $x(\lambda)$ is an object spectrum and n_i is the observation noise. Then, the output of the spectral detector is sampled in analog-to-digital converter and fed into a DSP unit to estimate the spectrum.

By collecting M samples, the data model for the output measurements, $\mathbf{y} \in \mathbb{R}^{M \times 1}$ can be represented as a system of linear equations:

$$\mathbf{y} = \mathbf{F}\mathbf{x} + \mathbf{n} \tag{1}$$

where $\mathbf{x}$ contains an $N \times 1$ vector of input spectrum sampled at wavelengths $\lambda_1, \lambda_2, \cdots, \lambda_N$ and $\mathbf{n}$ is an $M \times 1$ noise vector. Let $\mathbf{F}$ denote an $M \times N$ filter transmission function matrix, which is obtained by uniformly sampling the TFs, $f_i(\lambda)$, at wavelengths $\lambda_1, \lambda_2, \cdots, \lambda_N$. Each row of $\mathbf{F}$ represents a sampled TF of a filter.

We note that the number of spectral components of $\mathbf{x}$ is generally greater than the number of filters, i.e., $N > M$. Then, Eq. (1) becomes underdetermined and thus has infinite many solutions. However, if the input spectrum is represented by a sparse spectrum which contains a small number of non-zero components, the underdetermined system of Eq. (1) can be solved uniquely by modern DSP algorithms [9-10]. For a sparse representation of the input spectrum, we model the input spectrum $\mathbf{x}$ in Eq. (1) as a linear combination of basis functions, i.e., $\mathbf{x} = \mathbf{G}\mathbf{s}$ where $\mathbf{s} \in \mathbb{R}^{P \times 1}$ is a K-sparse spectrum with $K << P$ non-zero components. In this paper, we choose Gaussian kernels as basis functions since the Gaussian shape can preserve the smooth features of the spectra and requires only two parameters: the central location and width [6-7]. In Fig. 1(a), a Gaussian curve is shown with the central location of 800 nm and the full-width at half-maximum (FWHM) of 40 nm. In Fig. 1(b), a smooth spectrum can be expressed as a linear combination of three Gaussian curves with FWHM of 40 nm and central locations of 800, 860 and 900 nm. The kernel matrix $\mathbf{G} \in \mathbb{R}^{N \times P}$ is a set of the Gaussian curves each of which forms a column of $\mathbf{G}$. According to the nature of TFs of the filter-array and the nature of the object spectrum for a particular application, the number, locations, and FWHMs of Gaussian curves can be determined.



(a) (b)

Figure 1. (a) A Gaussian kernel with FWHM of 40 nm and center location of 800 nm (b) an example of sparse representation of object spectrum

Now, using the sparse representation of the input spectrum, $\mathbf{x} = \mathbf{G}\mathbf{s}$, Eq. (1) can be rewritten as

$$\begin{aligned}\mathbf{y} &= \mathbf{Fx} + \mathbf{n} = \mathbf{FGs} + \mathbf{n} \\ &= \mathbf{As} + \mathbf{n}\end{aligned} \tag{2}$$

where $\mathbf{A} = \mathbf{FG}$ represents an $M \times P$ measurement matrix. In order to reconstruct **s** from **y** given **F** and **G**, we use L_1 norm minimization algorithm with a non-negative constraint, derived in [5]. The L_1 norm minimization for the reconstruction of the sparse spectrum **s** in Eq. (2) can be expressed as

$$\hat{\mathbf{s}} = \min_{\mathbf{s}} \|\mathbf{s}\|_1 \quad \text{subject to} \quad \|\mathbf{As} - \mathbf{y}\|_2 \le \varepsilon, \mathbf{s} \ge 0 \tag{3}$$

where ε is a small positive constant. From the estimate of the sparse spectrum $\hat{\mathbf{s}}$, the input spectrum can be reconstructed by $\hat{\mathbf{x}} = \mathbf{G}\hat{\mathbf{s}}$. If the input spectrum is reliably reconstructed with $P > M$, the spectrometer can achieve resolution improvements.

In the framework of spectrum reconstruction in Eq. (3), it is important to design a good TF matrix **F** for the reconstruction of the sparse spectrum with high accuracy. Designing a good TF matrix **F** resembles designing a good measurement matrix in compressed sensing (CS). In CS, the mutual coherence (μ) of the measurement matrix **A** is defined as follows:

$$\mu = \max_{i \ne j} \left| \langle a_i, a_j \rangle \right|, \quad i, j = 1, \cdots, N$$

where a_i is the i^{th} column of **A** [11]. The mutual coherence represents the maximum possible correlation of among pairs of columns of **A**. The smaller μ means the smaller the correlation among the columns of **A** is. The smaller the correlation is, the better reconstruction accuracy of **s** from **y**. In CS, it is desirable to design the TF matrix **F**, such that the measurement matrix $\mathbf{A} = \mathbf{FG}$ has low coherence.

It is well known in CS that measurement matrices **A**, the entries of which are drawn from i.i.d. samples of a random variable, exhibit low coherence. Such matrices are called random measurement matrices. These matrices are capable of capturing enough information about the signal **s** to perform reconstruction from a small number of samples of **y**. Therefore, random measurement matrices are widely employed in CS-based applications. In [6], random TF filters were introduced in order to enhance the resolution of the spectrometers. In the deposition of the optical thin-film, however, the thickness and the refractive index of each filter are limited in practice, and thus such random TF filters are impractical and non-reproducible due to large tolerance of fabrication. We, thus, propose a realistically implementable design of filters which have a low coherence for resolution improvements.

3. DESIGN OF THIN-FILM FILTERS

We propose a design of a thin-film optical filter consisting of multiple layers of high- and low-refractive index materials deposited on a substrate. The transmittance spectra of multilayered dielectric filters were calculated by transfer matrix method [12]. For achieving incoherence among columns of **A**, the difference between the high- and low-refractive indices should be high and the number of pairs should be large. In this paper, SiN_x is used for a high-refractive index material and SiO_2 for a low-refractive index material. As shown in Fig. 2(a) filters are considered, each of which is composed of eight pairs of SiN_x and SiO_2. Note that increasing the number of pairs of layers leads to broadening the range of transmission of the filter. In order to reduce coherence among columns of **A**, each filter is designed to have different thicknesses of layers. The resultant thicknesses of layers in each filter are less than few micrometers. An example of the transmission spectra designed by the proposed method is shown in Fig. 2(b). The rates of transmission of filter 5 and filter 24 are highly uncorrelated.

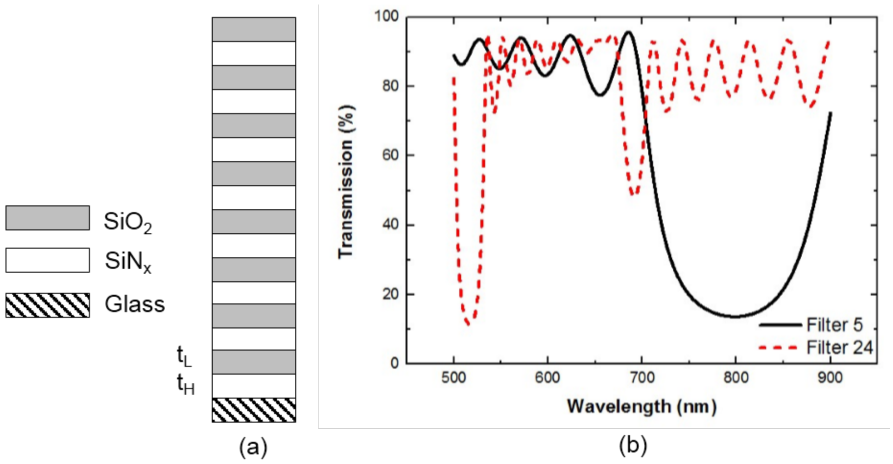


Figure 2. (a) Design structures of dielectric filters (b) Transmission spectra of filter 5 and 24

4. RESULTS

In this section, we aim to demonstrate the performance of spectrum reconstruction with a spectrometer consisting of the proposed filter array and the DSP algorithm. We consider the spectrometer with M = 64 filter elements in the filter array. The filters are designed as explained in Section 3. The wavelength range of interest is from 500 nm to 1100 nm. The length of spectral components is set by N = 600. As input spectra, we first consider a synthetic signal with two neighboring spectral components to identify the achievable resolution. We then evaluate the performance of the spectrometer for a spectrum of a halogen lamp, which has a broadband spectrum. The noise variance in Eq. (1) is assumed to be 0.01. As a kernel matrix, **G**, we choose Gaussian curves with FWHM of 4, 10, 20, 40, 60, 80 and 100 nm. Between 500 and 1100 nm, the Gaussian curves are evenly-located with 5 nm spacing for FWHM of 4 nm and with 20 nm spacing for the rest. A set of 300 Gaussian curves (P=300) forms the kernel matrix, **G**.

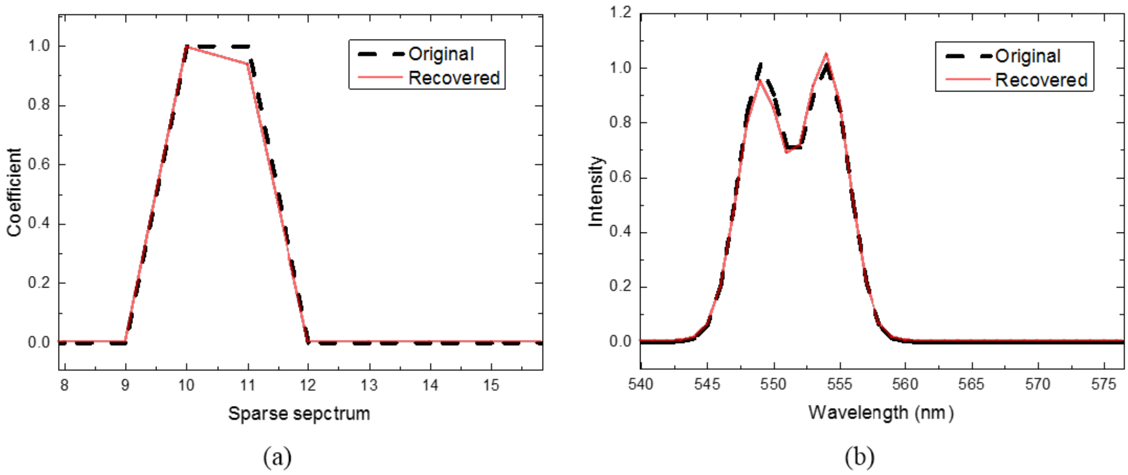


Figure 3. Narrowband spectrum reconstruction: (a) estimated sparse spectrum ($\hat{\mathbf{s}}$), (b) reconstructed signal spectrum ($\hat{\mathbf{x}}$).

In Fig. 3, we choose K = 2 sparse spectrum to see if two closely spaced spectral components can be resolved or not. The sparse spectrum **s**, has non-zero values at 10th and 11th elements. Accordingly, the input spectrum contains two dominant spectral components located at 550 nm and 555 nm, respectively. It is evident from Fig. 3(b) that the dominant spectral components are clearly resolved by the proposed spectrometer.

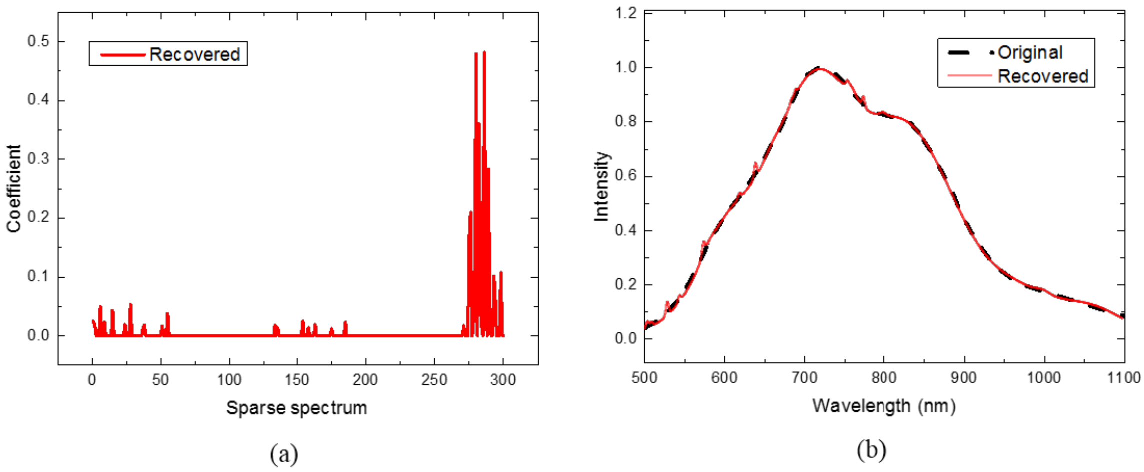


Figure 4. Wideband spectrum reconstruction: (a) estimated sparse spectrum ($\hat{\mathbf{s}}$), (b) reconstructed signal spectrum ($\hat{\mathbf{x}}$).

We now investigate the reconstruction performance with a broadband spectrum of a halogen lamp. The spectrum is measured by a high-resolution spectrometer for a reference signal spectrum. The original signal spectrum in Fig. 4 (b), can be reconstructed as a sparse spectrum with K = 34 in Fig. 4 (a). From $\hat{\mathbf{s}}$, the signal spectrum ($\hat{\mathbf{x}}$) is obtained by $\hat{\mathbf{x}} = \mathbf{G}\hat{\mathbf{s}}$.

5. CONCLUSIONS

In this paper, we have proposed a design of filters with low coherence to improve the resolution of a spectrometer. The optical filters are design by thin-film technology with efficiently feasible parameters. The proposed filter-array based spectrometer is incorporated with the DSP algorithm for resolution improvements. We have shown that the proposed spectrometer incorporated with the DSP algorithm, is able to resolve the spectral components that are more than 5 nm apart. By choosing the **G** appropriately, the spectrometer can reconstruct the broadband spectrum as well.

ACKNOWLEDGEMENT

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (No. APPL-201502-00558).

REFERENCES

[1] Brady, D.J., [Optical Imaging and Spectroscopy], John Wiley (2009).

[2] Parrein, P., Landragin-Frassati, A. and Dinten, J. M., "Reconstruction method and optimal design of an interferometric spectrometer." Appl. Spectroscopy, 63(7), 786-790 (2009).

[3] Wang, S. W., Xia, C., Chen, X. and Lu, W., "Concept of a high-resolution miniature spectrometer using an integrated filter array," Opt. Lett., 32(6), 632-634 (2007).

[4] Chang, C. C., Lin, N. T., Kurokawa U., and Choi, B. I., "Spectrum reconstruction for filter-array spectrum sensor from sparse template selection," Opt. Eng., 50(1), 114402/1-114402/7 (2011).

[5] Oliver, J., Lee, W.-B., Park, S. and Lee, H.-N., "Improving resolution of miniature spectrometers by exploiting sparse nature of signals," Opt. Exp., 20(3), 2613-2625 (2012).

[6] Oliver, J., Lee, W.-B. and Lee, H.-N., "Filters with random transmittance for improving resolution in filter-array-based spectrometers," Opt. Exp., 21(4), 3969-3989 (2013).

[7] Kurokawa, U., Choi, B. I. and Chang, C.-C., "Filter-Based Miniature Spectrometers: Spectrum Reconstuction Using Adaptive Regularization," IEEE Sensor J., 11(7), 1556-1563 (2011).
[8] Macleod, H. A., [Thin-Film Optical Filters], Institute of Physics Publishing (2002).
[9] Donoho, D. L., "Compressed sensing," IEEE Trans. Inf. Theory, 52(4), 1289-1306 (2006).
[10] Baraniuk, R., "Compressive sensing," IEEE Sig. Proc. Mag., 24(4), 118-121 (2007).
[11] Bruckstein A. M., Donoho, D. L. and Elad, M., "From sparse solutions of systems of equations to sparse modeling of signals and images," SIAM Rev. 51(1), 34-81 (2009).
[12] Pedrotti, F. L., Leno, S. J. and Pedrotti, S., [Introduction to Optics], Prentice Hall (2007).