Multispectral Imaging with Tunable Plasmonic Filters

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Supporting Information

ABSTRACT: We present an angle-insensitive, miniaturized and integratable filtering system based on plasmonic substrates for multispectral imaging. Active tunability of the plasmonic filter allows color recording, estimation of unknown spectra, and determination of spectral singularities, for example, laser lines, while exploiting the full spatial resolution of a B/W conventional camera. Compared to other multispectral imaging systems, the plasmonic filtering system can be placed in front of an existing imaging system, for example, including lenses, supporting a cost-efficient fabrication and integration. Additionally, it is characterized by high angular acceptance, which we demonstrate by imaging with a field-of-view of ~50°. Further, the number of nonpixelated broadband filters could be varied in situ for faster imaging or higher quality, compared to systems with a fixed number of channels.

KEYWORDS: plasmonic nanostructures, active tunable plasmonic filters, multispectral imaging, variable color filter, color recording, spectral reconstruction, laser detection

Currently the demand for imaging systems providing spectral analysis is strongly increasing.1,2 Recent markets include remote sensing3, food monitoring4, medical monitoring5, or art conservation.6 A diversity of instruments with unique performance is already available. Each of these techniques has its advantages and drawbacks, providing solutions mostly for niche applications. Important performance characteristics are the spectral, spatial, and temporal resolution. The field-of-view (FOV) defines the angular range that can be recorded by the camera. Finally, the bulkiness, handling, and expense are practical characteristics that strongly limit the range of applications.

The recording of the hyper- (>10 bands) or multispectral data can be done by spectral scanning (e.g., tunable filters7 or liquid crystal tunable filters8) or spatial scanning (e.g., gratings9), see Figure 1a,b. This often requires bulky and heavy parts or significant volume for spectral filtering. Alternatively, the spectral data can be recorded instantaneously (snapshot),10 at the expense of spectral or spatial resolution (e.g., multispectral filter array11 or filtered lenslet array12), see Figure 1c. Such systems are typically part of an imaging system (see gray box) and cannot be integrated into or combined with other existing systems. Furthermore, these "snapshot systems" often make use of interferometric filters that strongly depend on the incident angle, thereby reducing the FOV.10,11,13 Also, the spectral resolution depends on the number of pixels or lines with different spectral filtering properties (filter array), which leads to increased complexity and cost of fabrication.10,11 On the other hand, spectral imaging systems based on liquid crystal tunable filters and filtered lenslet arrays are often complex, sensitive, and expensive.8,12

Figure 1. Overview of current methods for multi- and hyperspectral imaging: (a) spectral scanning while acquiring images, (b) spatial scanning (line- or point-wise) while recording spectra, and (c) obtaining an image with spectral information in a single snapshot. (d) Shows a scheme of our active tunable plasmonic filter, indicating the angle-stability, compactness of tuning, and adaptability to imaging systems (gray box).

There is great demand for miniaturized, cost-efficient, and integratable multispectral imaging systems.2,14 Such systems...
can be realized, for example, with tunable broadband filters with angle-insensitive transmission properties. \cite{15,16} Recently, systems based on colloidal quantum dots, vertical silicon nanowires, and plasmonic filter patches \cite{16,18-20} were presented. Generally, in these realizations, each pixel is addressed by a single filter, which limits the spatial resolution and increases the fabrication complexity.

Here we present a plasmonic multispectral imaging (PMSI) system based on active tunable plasmonic filters (TPFs). These filters can be used as add-ons to existing commercial imaging systems (e.g., B/W or RGB camera). The working principle of TPFs is similar to variable filters, with the difference that the filter properties can be tuned by the polarization and not the structure itself (see Figure 1d). This leads to higher compactness and lower fabrication costs. Furthermore, it is designed to be nearly completely angle-insensitive in all directions, enabling a high FOV of $\sim 50^\circ$. The thickness of the plasmonic filters is in the range of a few micrometers, making them attractive for miniaturized systems. Furthermore, the filters are lightweight and robust. Similar plasmonic filters often suffer from structural and fabrication complexity, angle-sensitivity, limited active tunability, or low transmission.\cite{21-24}

They also maintain the full spatial resolution and are cost-efficient, which sets them apart from snapshot systems. Compared to spectral estimation using RGB cameras, no prior knowledge of the spectral reflectance or analysis of training samples is required.\cite{13,25}

The TPF is based on periodic silver nanowires; it is fabricated by replication of a master structure (nanostructures with 160 nm period and 70 nm depth) in sol–gel, evaporation of a thin layer of silver (30 nm), and subsequent embedding in sol–gel (see Figure 2a).\cite{26} The plasmonic substrate is finally placed between two polarizers; an input polarizer fixed at $45^\circ$ to the silver nanowires and an analyzing polarizer which can be rotated, see Figure 2b. Light transmitted through the input polarizer can be described as a combination of s- and p-polarized light incident on the sample (plane of incidence perpendicular to the nanowire lines). The p-polarized light excites a plasmon resonance,\cite{27} at which a wavelength-dependent phase shift is induced.\cite{28} Rotation of the subsequent analyzing polarizer (angles bold) leads to four main transmission spectra with a crossover at the plasmon resonance and angular combinations thereof (see Figure 2d).\cite{29} The TPF has $\pi$-rotation symmetry and its transmission, $T_{TPF}(\lambda, \varphi)$, depends on the rotation angle $\varphi$ of the polarizer. The number of angle settings ($\varphi_B \rightarrow \varphi_M \rightarrow \varphi_A$) defines the number of filters $M$.

A scheme of the system is shown in Figure 2c (a photo of the setup is shown in Figure S1a). A source with spectrum $I(\lambda)$ illuminates the sample to be measured. The reflected light, with intensity $R_{\text{pixel}}(\lambda)$, transmits through the TPF with $T_{TPF}(\lambda, \varphi)$, before an intensity image, $V_{\text{pixel}}(\varphi)$, is recorded by a camera with a given sensitivity $S(\lambda)$, see Figure S1b,c. The intensity of the image is extracted for each pixel and used to reconstruct the spectral information of the observed object, see Figure 2e. In the following experiments a black and white (B/W) camera is used, but our formalism is also valid for multispectral cameras that feature multiple spectral sensitivities $S$. To calculate the reflected spectra (reconstruction) the continuous spectral range $\lambda$ is divided into $N$ discrete regions. The recorded intensity of each pixel ($V_{\text{pixel}}$) can be approximated as a discrete function of the wavelength $\lambda_n$ as

$$V_{\text{pixel}}(\varphi_m) = \sum_{n=1}^{N} S(\lambda_n) \times I(\lambda_n) \times T_{TPF}(\lambda_n, \varphi_m) \times R_{\text{pixel}}(\lambda_n)$$

$$A(\lambda_n, \varphi_m)$$

Every image pixel ($ij$) has its own value of $V_{\text{pixel}}$ and $R_{\text{pixel}}$. $S$, $I$, and $T_{TPF}$ are the same for all pixels. They depend on the wavelength $\lambda_n$ and the rotation angle of the filter $\varphi_m$ and need to be evaluated only once for a given illuminant. The number of discrete frequency regions ($N$) defines the number of unknowns when solving for $R_{\text{pixel}}(\lambda_n)$. On the other hand, the number of filters ($M$), expressed by the discrete rotation angles $\varphi_B \rightarrow \varphi_M \rightarrow \varphi_A$, determines the number of known variables. This leads to a linear system of equations $V_{\text{pixel}}(\varphi_m) = A(\lambda_n, \varphi_m) \times R_{\text{pixel}}(\lambda_n)$ with $M$ known and $N$ unknown variables. Solving this linear equation renders the spectrum $R_{\text{pixel}}(\lambda_n)$ for every image pixel. To solve for $R_{\text{pixel}}(\lambda_n)$ we use the linear least-squares approximation,\cite{28} which minimizes the squared Euclidean norm of
\[
\min_{\mathbf{R}} \frac{1}{2} \| \mathbf{A}(\lambda_n, \phi_m) \times \mathbf{R}_{\text{pixel}}(\lambda_n) - \mathbf{V}_{\text{pixel}}(\phi_m) \|^2 
\]  

(2)

If the matrix \( \mathbf{A}(\lambda_n, \phi_m) \) had full rank, meaning that all the included filters are linearly independent from each other, the system of equations could be solved completely and with high accuracy. On the other hand, if a set of filters with low rank is used the solution can become inaccurate or unstable (its values oscillate), especially if the system is disturbed by perturbations (e.g., noise). To evaluate the linear dependence of the filters, a singular value decomposition (SVD) of the matrix \( \mathbf{A}(\lambda_n, \phi_m) \) has been performed. It shows that the first three eigenvalues yield the strongest contribution; the corresponding eigenvectors can reproduce the system nearly entirely. Thus, most colors can be reproduced with only three filters. However, reconstruction of spectra with singular features (e.g., laser lines) require a larger set of filters. A detailed discussion about the necessary number of eigenvectors for spectral estimation, as well as an in-depth comparison to RGB cameras, is given in the Supporting Information.

For comparison reasons, all our spectral reconstructions were done with the same least-squares algorithm. Furthermore, for simplicity we take a large number of filters \( M \) greater or equal to the number of spectral regions \( N \). We note that results can be improved by principle component analysis\(^{13,30} \) or by Wiener estimation,\(^ {25,31} \) which would additionally decrease the computation time. However, such optimizations are beyond the scope of this paper.

As a test target, we use a Macbeth ColorChecker. B/W images of colored patches are recorded using a commercial LED light source in combination with our PMSI. The reconstructed spectra are then compared with the spectra directly measured with a conventional spectrometer (see Figure 3). To analyze the FOV of the imaging system the analysis was done for tilt angles of 0, 15, and 25°. For all these angles, the reconstructed spectra reproduce the reference spectrum very well. The color representation (insets in Figure 3) is also excellent, even for large tilt angles. Residual deviations from the reference spectrum and oscillations in the spectra likely arise from the reconstruction procedure (also discussed by Bao et al.\(^ {15} \)) or from the linear dependence of the filters (see before).

Overall, the results indicate that our PMSI operates reliably for a wide range of angles, enabling acceptance angles of more than \( \sim 50^\circ \), which corresponds to a minimum \( f \)-number of \( f/1.07 \) (the range of conventional lenses). Figure S3 shows the measured colors in a CIE color plot and Table S1 displays the corresponding RMS and color difference.

Our imaging experiments are performed with the PMSI featuring a standard B/W camera (see Figure 4). For each pixel of the recorded image, a spectrum \( \mathbf{R}_{\text{pixel}}(\lambda_n) \) is reconstructed (Figure 4c), which is converted to a color (Figure 4b). We apply no further postprocessing (e.g., white balance, gamma correction, etc.). While the colors of the fruits are reconstructed very well, the white background in the image features a yellowish tint, which could originate from poor estimation of the illumination source and which could be eliminated by simple calibration. To reduce the computation time, the
resolution of the image was decreased by a factor 3. The spatial resolution is related to the unit cell size of the camera (here: 6.45 μm × 6.45 μm). The proposed method is based on zero order transmission and does not have color cross-talk, basically allowing the use of smaller unit cells. However, investigation of the spatial resolution limit is beyond the scope of this paper.

Finally, to further characterize the spectral recording capabilities, we utilized the PMSI to measure laser light with different emission wavelengths. Some of the reconstructed laser lines are shown in Figure 5b. The reconstruction accuracy is influenced by the local minima and maxima of the filters (see Figure 5a), which determine the calculation of the eigenvectors of the system. This makes it possible to find a unique solution with a high spectral resolution within a certain wavelength range (cf. discussion on RMS, SI, Figure S2). As shown in Figure 5c, our procedure is able to distinguish laser lines characterized with a spectral resolution of 2 nm. Figure 5d shows a comparison of the measured and expected laser peak position of the laser lines (inset: corresponding fwhm). Here $M = 180$ and $N = 180$.

In summary, we present a functional multispectral imaging system based on active tunable plasmonic filters and a commercially available black/white camera. We demonstrate the recording of colored objects and laser lines at full spatial resolution and without prior knowledge. This includes an estimation of the spectra for each pixel, capable of distinguishing two laser lines separated by 1 nm. The multispectral imaging system is largely angle-insensitive, allowing us to record images and spectra with a FOV of $\sim50^\circ$. The homogeneous and nonpixelated plasmonic filters can be fabricated with standard roll-to-roll techniques, enabling cost-effective manufacturing for a wide range of applications.

The spectral resolution and dynamic range could be improved if a camera with multispectral arrays (e.g., RGB camera) was used. The number of used filters, as well as the spectral estimation algorithm, could be adapted in situ, depending on the kind of application, for example, analysis of artworks, remote sensing, and so on. To cover other spectral ranges (e.g., infrared), one can adapt and optimize the plasmonic structures. A variety of such plasmonic structures could be designed as filter arrays to increase the spectral resolution or to use the camera in single-shot imaging mode. Besides a high FOV and low fabrication cost, such a multispectral filter array would strongly decrease the recording time. Also, the rotating polarizer can be replaced by an electrically tunable liquid crystal, which would facilitate the integration into miniaturized and lightweight systems, for example, lab-on-a-chip applications. Further development of the solving algorithm can also greatly enhance the spectral resolution of the system. This could include a correction/calibration matrix, appropriate boundary conditions, or databases of known substrates.

### MATERIALS AND METHODS

#### Fabrication and Arrangement of the Plasmonic Tunable Filter

After fabrication of the plasmonic filter, a wire grid polarizer (ITOS, XP44) was glued diagonally to the nanowires onto the sample. This substrate was then fixed onto a holder just in front of an automatic rotation stage (Thorlabs, PRM1/MZ8) containing a wire grid polarizer (ITOS, XP44). Rotation of this polarizer enabled different transmission spectra of the active tunable plasmonic filter (TPF).

#### Measurement Setup

The TPF was characterized by direct illumination of collimated light (Mikropack, DH-2000) and a spectrometer (Photoresearch, SpectraScan 735). A transmission spectra was recorded each 1° and calibrated by the measured light source. The maximum transmission through the used TPF was 0.064, by which the transmission spectra were normalized. For image recording, the plasmonic filter was mounted in front of a black/white camera (Baumer TXG14, silicon sensor) with configurable macro lens (Opto Engineering, MC3-03X). The setup used a field of view at a distance of about 50 cm, which was illuminated with a LED screen (Dörr, DOI: 10.1021/acsphotonics.6b01003 ACS Photonics 2017, 4, 236–241
Images were recorded with a homemade LabVIEW (version 2015) script, while controlling the filter angle. To compare the accuracy of the spectral reconstruction, the colored patches of the Macbeth ColorChecker (X-Rite) were measured with the spectrometer directly.

**Reconstruction Software.** The recorded images were imported in a homemade MATLAB (version 2016) script. The intensity of the pixels of interest were extracted correspondingly for each used filter angle. For analyzing the color patches, an average of 100 × 100 pixels was taken. Additionally, the measured spectra of the TPF and light source and the sensitivity of the camera has to be imported. For simplicity reasons, a linear intensity-response behavior of the camera sensor was assumed. Then MATLAB (version 2016) was used to perform an iterative least-squares fit (command: “lsqin”, see https://ch.mathworks.com/help/optim/ug/lsqlin.html) with boundary conditions of a certain wavelength range scaling. The solution was limited to positive values only, with the upper boundary limiting it to physical useful values. A smoothness filter (command: “smooth”), https://ch.mathworks.com/help/curvefit/smooth.html, moving average: 5) was applied to the reconstructed spectra to reduce oscillation effects arising from the ill-condition problem. The resulting spectra were converting into RGB values (CIE 1931 color space, homemade MATLAB script), which were then plotted as color images.

**Imaging Experiment.** The reconstruction was done with the same parameters as the measurement of the ColorChecker. To reduce computation time of the not optimized algorithm the image was reconstructed by averaging 3 × 3 adjacent pixels of the recorded image leading to a final image resolution of 434 × 267 pixels. The sample was illuminated with the LED screen (Dörr, LP400) at a certain distance to ensure homogeneous illumination. An exposure time of 3 s was used.

**Laser Measurements.** A tunable laser (NKT Photonics, SuperK EXW-12) was used to illuminate a scattering white surface (Thorlabs, EDU-VS1). The images thereof were recorded, and by using the same algorithm as before, the laser lines were reconstructed.

**ASSOCIATED CONTENT**

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acsphotonics.6b01003.

Figure S1, showing details of the setup. A short section describes more in detail other reconstruction techniques such as principle component analysis and Wiener estimation and compares the proposed system with RGB cameras. Figure S2 shows the effect of the number of eigenvectors used for reconstruction. Figure S3 shows the measured colors of Figures 3 and 5 in a CIE color plot; Table S1 shows a comparison of the color difference thereof (PDF).

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**Notes**

The authors declare no competing financial interest.

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**ABBREVIATIONS**

fwhm, full width at half-maximum; TPF, active tunable plasmonic filter; PMSI, plasmonic multispectral imaging; B; W, black and white; FOV, field-of-view

**REFERENCES**

Supporting Information – Multispectral Imaging with Tunable Plasmonic Filters

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Supporting Information including:
6 pages with 3 figures
1. Setup of the Plasmonic Multispectral Imaging System

Figure S1a shows a photo of the plasmonic multispectral imaging (PMSI) system. The spectra of the light source and the sensitivity of the B/W camera are given in Figure S1b. Figure S1c shows two photos of the color checker board (Figure S1a, left side), which are recorded at different angles. The red rectangles highlight the area, which was used to reconstruct the color.

**Figure S1.** (a) Photo of the PMSI including the B/W camera, the lens system, the variable polarizer mounted on a rotation stage, the plasmonic substrate with a fixed polarizer and the color checker board, from right to left. (b) Spectra of the LED light source (LP400) and the sensitivity of the B/W camera (TXG14). (c) Intensity images of the color checker board (see (a) left side) at different rotation angles $\varphi = 0^\circ$ and $90^\circ$ of the variable polarizer. Measurement areas are marked with red rectangles.
2. Comparison to RGB imaging systems

Most common and cost-efficient imaging systems contain only few channels (e.g. RGB camera). There are several existing algorithms to estimate higher dimensional spectra out of limited data. Most of the methods require prior spectral analysis to optimize the set of filters or to more accurately reconstruct a subsampled stimulus.\(^1\) The most popular algorithms are principle component analysis and Wiener estimation. They are based on reducing the dimension of training samples and using the eigenvectors for reconstruction\(^2\) or constructing a transform matrix for reproduction of training samples, respectively.\(^3\) Such system can be very versatile for spectral reconstruction, but unfortunately require prior knowledge about the spectral reflectance of the sample or training samples, which limits the usability and range of applications. Several improvements were made to optimize the reconstruction accuracy and time, but they are often optimized for certain problems.\(^4,5,6,7,8\)

Overall the proposed PMSI has similarities to other multi-channel imaging system, e.g. RGB camera. Even though it has a high number of possible filters, it mainly consists out of 3 independent filters (eigenvectors) similar to an RGB system. This limits the resolution of the spectral reconstruction. Nevertheless more filters are useful because: a) spectral reconstruction can be done directly and not by using an estimation algorithm (e.g. Wiener estimation) requiring training samples, b) depending on the measured reflection, the system is solved by distinct eigenvectors, enabling detection of e.g. spectral singularities, c) they reduce random noise, leading to a more stable solution during reconstruction. Here the filters are mounted before the camera system, which in contrast to e.g. RGB camera enables recording of images at full spatial resolution. This enables adaptive exchange of the filter or combination with existing (multispectral) camera system. In contrast to other multispectral system the number of filters (and recording time) can be selected actively depending on the applications (spectral vs. temporal resolution). Finally, RGB filters are designed for colorimetric measurements; the filters are separated to be linear independent and overlap for e.g. color filter array interpolation (so-called demosaicing).\(^9,10\) The here proposed filters have a high spectral overlap; this could be beneficial for accurate detection of spectral features, whereas a higher number of filter could be required for accurate colorimetric measurements.
3. Number of required eigenvectors for reconstruction

To give an estimate on the number of necessary eigenvectors, we can reproduce a given spectra $R_{\text{original}}$ with a certain number of corresponding eigenvectors $U$ of $T_{\text{PTF}}$:

$$R_{\text{reproduced}} = U * U' * R_{\text{original}}. \quad (1)$$

Figure S2 shows the root mean square (RMS) of the difference between $R_{\text{reproduced}}$ and $R_{\text{original}}$ of equation (1) versus the number of eigenvectors used. The eigenvectors were used in decreasing independency order. The graph clearly shows that for color patches (e.g. MacBeth ColorChecker) mostly 3 eigenvectors is sufficient to achieve a small RMS, whereas for laser lines, especially the ones located further away from the plasmon resonance (~490nm) a higher number of eigenvectors is required. Overall such a system should include as many eigenvectors as necessary, without losing spectral reproducibility, but also as little as possible to decrease complexity and speed of the solving algorithm.

![Figure S2](image)

**Figure S2.** The RMS compared to the number of eigenvectors. For colored patches the RMS decreases faster with less eigenvectors as for the laser lines, especially when the laser lines are located further away from the plasmon resonance (~490nm).

4. Color plot of measured color patches and laser lines

Figure S3 shows a CIE xyY color plot (CIE 1931 color space)\textsuperscript{12} including the angle-dependent measured colors of Figure 3 and the measured laser lines of Figure 5. Table S1 gives an overview of the color difference (CIE $\Delta E$ 2000)\textsuperscript{13} and corresponding RMS of the color patches.

![Color plot of measured color patches and laser lines](image)

**Figure S3.** CIE color plot including the measured samples. The white ellipse embrace each the same colored patch measured at different tilt angles including the reference. The black dots indicate the measured position of the laser.

<table>
<thead>
<tr>
<th>Patch</th>
<th>CIE $\Delta E$ 2000</th>
<th>RMS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0° 15° 25°</td>
<td>0° 15° 25°</td>
</tr>
<tr>
<td>Red</td>
<td>5.1 1.5 10.9</td>
<td>0.10 0.10 0.12</td>
</tr>
<tr>
<td>orange</td>
<td>9.5 4.4 14.2</td>
<td>0.12 0.15 0.16</td>
</tr>
<tr>
<td>yellow</td>
<td>9.4 4.7 11.5</td>
<td>0.12 0.07 0.18</td>
</tr>
<tr>
<td>green</td>
<td>3.9 2.0 4.1</td>
<td>0.05 0.05 0.05</td>
</tr>
<tr>
<td>light blue</td>
<td>2.4 4.6 3.3</td>
<td>0.07 0.07 0.08</td>
</tr>
<tr>
<td>dark blue</td>
<td>14.1 14.8 4.5</td>
<td>0.11 0.09 0.06</td>
</tr>
<tr>
<td>purple</td>
<td>7.5 6.6 5.4</td>
<td>0.12 0.12 0.11</td>
</tr>
<tr>
<td>pink</td>
<td>3.8 5.0 3.5</td>
<td>0.09 0.15 0.10</td>
</tr>
<tr>
<td>black</td>
<td>3.6 3.5 4.5</td>
<td>0.01 0.01 0.01</td>
</tr>
<tr>
<td>white</td>
<td>7.2 11.0 8.6</td>
<td>0.07 0.12 0.15</td>
</tr>
<tr>
<td>Average</td>
<td><strong>6.7 5.8 7.1</strong></td>
<td><strong>0.09 0.09 0.10</strong></td>
</tr>
</tbody>
</table>

**Table S1.** CIE $\Delta E$ 2000 and RMS values of the color patch measurements upon tilt angles of 0°, 5° and 25°.
REFERENCES


