Real time implementation of matched filtering algorithms using adaptive focal-plane array technology

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ABSTRACT

Spectrally tunable quantum-dot infrared photodetectors (QDIPs) can be used to approximate multiple spectral responses with the same focal-plane array. Hence, they exhibit the potential for real time adaptive detection/classification. In the present study, it is shown that we can perform the detection/classification operation at the adaptive focal-plane array (AFPA) based on QDIPs by fitting the QDIP’s response to the correspondent operators. With a new understanding of spectral signature in the sensor space, the best fitting can be achieved. Our simulation results show how well QDIPs perform in different regions of the spectrum in the mid- and long wave infrared. The results indicate that the AFPA performance does not match that of the ideal filtering operators, but reliable measurement can be accomplished.

Keywords: Spectral Imagery, Quantum-Dot Infrared Photodetectors, Adaptive Focal-Plane Array, Adaptive Sensing

1. INTRODUCTION

Spectral imagery in the wavelength range of 4-20\textmu m has many practical applications, and there is therefore significant interest in developing novel devices operating in this spectral range. Devices based on intersubband transitions in quantum-confined heterostructures in III-V compounds can be used for IR detection. Quantum-dot infrared photodetectors (QDIPs) are expected to demonstrate better performance at elevated temperatures than quantum-well infrared photodetectors (QWIPs) or HgCdTe infrared photodetectors due to their favorable carrier dynamics. The main advantages of QDIPs include sensitivity to normal incidence photo-excitation undetectable by QWIPs, broader infrared response, higher photoconductive gain, increased extraction efficiency and much lower dark currents than QWIPs.\textsuperscript{1} Another useful characteristic of QDIPs for many applications is that they can exhibit spectrally tunable responses.\textsuperscript{2} As the bias voltage across the photodetector is changed, the spectral response curve of a spectrally tunable photodetector can be altered in a reproducible fashion. These responses can be used to approximate an arbitrary spectral response. The approximation can be achieved in two steps: First, a number of measurements are made with different bias voltages on the photodetectors. Second, the results of these measurements are linearly combined with a particular set of weights

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calculated beforehand to produce the desired spectral response. This would lead to a tunable sensor whose peak response wavelength and spectral resolution are electrically tuned in the range from 4 to 12 µm, suitable for carrying out the goal of an adaptive focal-plane array (AFPA).

The spectral pattern of the radiation from a scene is a vector in an infinite dimensional space which we can name as spectral space, while the true-data from a scene always lies in a subspace of the spectral space that includes all physically realized spectra. Spectral imagery is a process that projects the original spectral patterns into a sensor space spanned by the responses of the different bands of a sensor. Since the responses are also vectors in spectral space, the sensor space is also a subspace of spectral space. A necessary condition for good-quality spectral imagery is that the sensor space and the feature space be “close” in some sense. With typical hyperspectral instrument, this usually means that the intrinsic dimensionality of the sensor space should be much higher than the feature space, i.e. many narrow spectral bands, so that the instrument can capture the true-data rather than just present a lower-dimension projection of the feature space. Because the QDIP’s responses under different bias voltages are always highly correlated, we can use singular value decomposition to uncorrelate them to find out the intrinsic dimensionality of the QDIP’s space, which is a critical step to evaluate QDIP’s ability for spectral shift to capture the feature space.

The measurement process of the detector itself is a projection of the true-data to the sensor space, while some common detections/classification processes, like matched filtering (MF), orthogonal subspace projection (OSP) and linear unmixing (LU) algorithms, can be considered as further projection process. It is intuitive that if the detector’s response is equal to such a specific operator, the output of the detector is then the result of this algorithm. Since QDIP’s responses are bias dependent, we can use QDIP’s responses to fit these operators. Simulations based on this idea are shown using the QDIPs we fabricated previously. These simulations show how much the QDIP’s spectral characteristic influence the resulting images and how well QDIPs can be used for detection/classification.

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The paper represents a mathematical model for QDIPs’ remote sensing application and an attempt to describe the relationship among the ground truth, sensor space and post-processing algorithms. Section 2 presents the spectral features of QDIP we use for this test. The algorithms for detector’s feature-extraction and detection/classification operator simulation are provided in section 3. Section 4 contains a description of the AVIRIS data used for analysis and the simulation results calculated with ENVI 4.0. We will make further discussion on these results and draw some general conclusions in section 5.

2. QUANTUM-DOT INFRARED PHOTODETECTORS

The usual technique for the formation of quantum dots is based on self-assembly under highly strained epitaxial growth, such as molecular beam epitaxy (MBE). Under certain growth conditions, the epitaxial film thermodynamically prefers to minimize its free energy by assembling into three-dimensional islands, which are known as quantum dots. These structures can be formed using numerous semiconductor systems including as InGaAs/GaAs, SiGe/Si, and InGaAs/InP. We previously reported QDIPs in which the InAs dots are placed in an InGaAs well that is incorporated in a GaAs matrix. This dots-in-a-well (DWELL) detector provides better confinement for the carriers trapped in the quantum dots so that we can control the transition by varying the composition and the thickness of the InGaAs well surrounding the dots. The details of the device design and fabrication are discussed elsewhere.

Fig. 1 shows the normal-incidence spectral responses from a 10-layer InAs/In$_{0.15}$Ga$_{0.85}$As 100µm-aperture structure at 38K with different bias voltages and amplifier gains. We have measured 53 responses with bias voltages from -3V to 3V with 0.1V bias voltage intervals. Six of them are selected to demonstrate the spectral shift. The origin of the shift is due to the asymmetric design of the DWELL region. The InAs dots are placed in an InGaAs well, with well thicknesses
of 10Å and 60Å on either side of the dots.

Figure 1. Normalized QDIP spectral responses measured from a 10-layer InAs/In$_{0.15}$Ga$_{0.85}$As 100µm-aperture structure at 38K with selected bias voltages. The effect of atmospheric absorption is not removed.

There are three notable peaks in these response curves. For large positive voltages, typically greater than around 2V, the peak of the response occurs at around 7.6µm with a spectral width of about 2µm. A second peak around 10.6µm can also be seen, but is less significant. However, for large negative biases, this longer wavelength peak becomes the largest feature of the spectral response. For smaller negative and positive voltages, approximately between –2 and 2 V, a third peak in the range between 6 and 7 µm is clearly evident as the strongest peak. The experiment shows that the QDIP’s spectral response does change with bias voltage in a wide range from -3V to 3V and the responses change in a reproducible fashion.

Although QDIPs can show some spectral tunability, the number of response peaks is physically limited and the bandwidths of the response are wide so there are significant overlaps between these responses at different bias voltage. This is a disadvantage for multispectral or hyperspectral measurement where very high spectral resolution is required. New QD manufacture techniques are developing for more significant spectral shift. However, in many applications, extremely fine spectral resolution is not necessary. A proper post-processing algorithm is developed in order to show how to utilize QDIPs in a more useful way.

3. MATHEMATICAL MODEL FOR SPECTRAL SENSOR

The reflectance spectrum of one material is usually a plot of the fraction of radiation reflected as a function of the incident wavelength and serves as a unique pattern for this material called the spectral signature. Spectral imagery is the process to measure the reflecting radiance pattern from a scene and find out the ground truth through the image. The imagery process is always carried out by a sensor with many bands and we can use the series of output of these bands to approximate the spectral pattern of the incident light. It must be emphasized that these bands are not restricted to be narrow spectral bands with monotonically increasing center wavelengths as we are accustomed to. The spectral pattern of a scene can be reconstructed through any combination of different spectral responses.

For any given measurement process, the photocurrent of photodetector is the product of the detector response and incident spectrum. For a broadband measurement, the photocurrent is the integral of the product through the wavelength
\[ i = \int_{\lambda_{1}}^{\lambda_{2}} l(\lambda) r(\lambda) d\lambda \]

where \( l(\lambda) \) is the spectral radiance and \( r(\lambda) \) is the detector response. In spectral imagery processing, we often consider the output from sensor as a vector in hyperspace. In fact, the spectral pattern from a scene itself is such a vector \( l \) belonging to an infinite-dimensional continuous function space named spectral space. Then the output current for one band is

\[ i \rightarrow \sum_{j=1}^{\lambda_{2}} l(\lambda) r(\lambda) = r^{T} l \]

Any physical variable with spectral pattern is a vector inside the spectral space, as is the spectral response of the detector. Like spectral vector \( l \), we can define the detector response as a vector \( r \) and consider the photocurrent \( i \) as the inner product of the incident radiance vector \( l \) and response vector \( r \). The inner product of two vectors represents a projection from one to the other geometrically. It means that the output current is a projection result.

All spectral sensors include many spectral bands. Since each band’s spectral response is a vector in the spectral space, these vectors span a subspace of that, which we define as sensor space. Each band is a basis of this sensor space. Since the spectral response is changing with the bias voltage for QDIPS, we can define a response under certain bias voltage as a QDIP’s band. Switching the bias voltage is then switching the band. Let \( k \times p \) matrix \( R \) be the sensor spectral response matrix representing the sensor space, where \( p \) is the number of sensor bands and the number of rows \( k \) should be infinite theoretically. Each column of \( R \) represents a spectral response of a QDIP’s band. Without loss of generality, these columns can be correlated or even linearly dependent with each other. The output is then

\[ I = R^{T} l + n \]

where \( n \) is a \( p \times 1 \) noise vector representing noise. The output photocurrent of each band is the projection from \( l \) to a basis so that the total measurement result of the sensor is the projection from \( l \) to the sensor space. For a specific material, or a class, with stamped spectral pattern in spectral space, the projection result \( I \) to the same sensor space is identical. We name it signature, which is a more general definition. For different sensors, the signatures of same class are usually different. This is shown in fig. 2 in a simplified manner.

**Figure 2.** One material class with stamped spectral pattern \( l \) is projected onto different sensor spaces and represented by different “signatures” \( I = [i_1, i_2] \) according to our definition. We assume the spectral spaces in (a) & (b) are of the same coordinates.

The feature space of a scene is a subspace of the spectral space and is independent of the sensor type. Any projection from the scene to the sensor space might lose some features. How much information is lost depends on the geometric relationship between the scene vectors and sensor space. In general, the more the sensor bands, the higher the
sensor space’s dimensionality, the less information is lost. For a hyperspectral sensor, the sensor space’s dimensionality is very high and the resolutions of bands are usually narrower than or equal to the spectral spacing so that the responses of different bands are spectrally continuous. We can say that the spectral pattern from a scene is precisely caught by this sensor and the outputs of different bands spell out the original signature, which is really a good approximation.

It is not the case for sensors with QDIP whose responses under different bias voltages are highly correlated. If these responses are also described as basis vectors, they do not span Cartesian coordinates. We can use singular value decomposition (SVD) to uncorrelate these responses

\[
R = USV^T
\]

and

\[
I = R^Tl + n = VS^TU^Tl + n
\]

\[
V^TI = (S^TU)^Tl + V^Tn = X
\]

where \(S\) is the singular value matrix of \(R\) and both \(U\) and \(V\) are orthogonal matrices. A sensor with response matrix \(R\) behaves the same way as an imaginary sensor with response matrix \(S^T U^T\) whose columns are orthogonal to each other. The \(p \times 1\) vector \(X\) is the output of this sensor, or the new signature. Obviously it is just a linear unitary transformation of original signature \(I\). Another useful result is that if noise is whitened before the SVD process, the noise level does not change in this transformation because \(V\) is a unitary matrix. All the transformed bands have the same noise level. This is what the minimum noise fraction (MNF) transform does.

Fig. 3 shows plots of the spectral responses of the QDIP we test and the equivalent sensor calculated through SVD. Fifty responses are selected and the reason for this number will be stated in section 4.

![Figure 3](image)

**Figure 3.** (a) QDIP’s responses measured from a 10-layer InAs/In\(_{0.15}\)Ga\(_{0.85}\)As 100\(\mu\)m-aperture structure at 38K. (b) SVD result of these responses. Note: the SVD results will change when different weights are applied to the original responses.

The column vectors of the left singular matrix \(U\) are unitary vectors uncorrelated with each other, reflecting the spectral shift of different QDIP bands, while columns of \(S^T U^T\) are the products of these column vectors multiplying with their correspondent singular value. As stated above, noise is still white in these bands after the SVD process, so the singular values are measure of the SNR for these transformed bands. For example, if all the SNRs of original QDIP bands are 100, the singular values for above bands are a series of numbers in descendant order: 646.99, 198.13, 116.81, 95.80, 80.97, 72.73, 45.07… These singular values are shown in fig. 4.
Figure 4. Singular values of QDIP’s response curves in a descendant order, which reflect the SNRs of uncorrelated bands calculated through SVD. They are calculated under the assumption that all the original bands of QDIP have SNRs of 40dB.

For this QDIP, the set of spectral response vectors lies in a fifty-dimensional subspace of the spectral space. The sensor space can be divided into two parts by an arbitrary threshold of the singular values of bands or SNR: one part associated with the large singular values and good quality responses, and a complementary part with small singular values and noise significant responses. When the singular values drop to be lower than the threshold, the correspondent transformed band is not counted as an efficient band, so the former part decides the intrinsic dimensionality of the sensor. For a QDIP, the number of the original bands simply depends on the number of bias voltages applied, but the intrinsic dimensionality depends on the QDIP’s spectral characteristics only. Note that these singular values depend on the SNRs of original responses which can be measured practically. Correlated original responses will give worse imagery result than uncorrelated ones when the numbers of bands and SNRs of each band are same.

4. SIMULATION RESULTS FOR AFPA

Based on the understandings of sensor-band, signature and image, we can calculate all detection/classification operators for a QDIP according to their definitions.\(^7^9\) The simulation shows these operators are different in numbers for different sensors but equivalent for imagery. The scene chosen for this simulation, which can be found in ENVI 4.0 complementary data CD 2, is from the 1995 AVIRIS reflectance data of Cuprite, Nevada. The data has been EFFORT polished and ATREM-calibrated. This AVIRIS subset covers spectral range from 1.99µm to 2.40µm in 50 spectral bands with approximate 10nm width each. The ground truth of the scene has been well investigated so the signatures of main classes are known, which can also be found in the same CD. Although they are already projected data from the original scene to the AVIRIS sensor, SNRs throughout this spectral range are so high that little information is lost in this projection process. We can consider the data as the original spectral pattern from spectral space.

The spectral shift of the QDIP sensor we have is not concentrated on this narrow spectral range, but we cannot find suitable scene data in mid/long wave infrared range. We have chosen to linearly stretch the QDIP responses in wavelength range from 1.4µm-18µm to 1.70µm-2.60µm. This is equivalent to linearly stretch the scene’s spectral pattern to a wider range covering a majority of QDIP’s spectral response. The stretch is reasonable because only the digital numbers (DNs) of the images are used. The calculation is not related to the wavelength or bandwidth of each band.

Fifty response curves under different bias voltages or gains without noise estimation are selected for this simulation. The number is chosen to be the same as the AVIRIS data. For each response or each band, the output of the AFPA would be an image with inner product of the AVIRIS data and QDIP response as DNs of every pixel covering the same spatial
area. To make the production possible, interpolation was applied to the responses and it will deform the sensor space a little. By switching the band (bias voltage), 50 such images are calculated and we name them projected images. All the simulations are performed by IDL 6.0 and ENVI 4.0. Fig. 5 shows images from an AVIRIS band and a projected band. Mathematically, the projected images are just the linear transformations of the AVIRIS images. Since the spectral bands are defined in different manner for AFPA in this paper, the Z-profile of the projected image is a plot of DN changing with bias voltage rather than wavelength. All the spectral responses are normalized to highlight the spectral shifts.

![Figure 5. (a) Band 172 of AVIRIS sensor centered at 1.991µm. (b) Projected image of QDIP with the bias voltage -2.9V. (c) & (d) Z-profiles of the same pixel shown above for these two images. For AFPA, the abscissa of Z-Profile has the physical meaning of bias voltages. Z-profile in (d) shows some overlaps because some responses are measured with the same bias voltages but different gains.](image)

MNF transform is used in ENVI to estimate the noise and find out the intrinsic dimensionality of the image. The MNF results of the original AVIRIS images and AFPA projected images are shown in table 1. They are almost equal to each other regardless of the round-off error. The correspondent first-band MNF images and the 2-D scatter plots between them are shown in fig. 6. They are purely inverted because the QDIP’s first transformed band shows negative response.

<table>
<thead>
<tr>
<th>MNF Band</th>
<th>Eigenvalue for AVIRIS images</th>
<th>Eigenvalue for projected images</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>39.08719</td>
<td>39.08582</td>
</tr>
<tr>
<td>2</td>
<td>31.44829</td>
<td>31.4457</td>
</tr>
<tr>
<td>3</td>
<td>22.99853</td>
<td>22.99872</td>
</tr>
</tbody>
</table>
Table 1. Eigenvalues of the first 5 MNF transformed bands

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<tr>
<th></th>
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<tbody>
<tr>
<td></td>
<td>9.799793</td>
<td>9.799081</td>
</tr>
<tr>
<td>5</td>
<td>6.563126</td>
<td>6.563272</td>
</tr>
</tbody>
</table>

Figure 6. (a) The first-MNF-band image of the AVIRIS images. (b) The first-MNF-band image of the projected images. (c) 2-D scatter plot between (a) and (b). (d) 2-D scatter plot between second-MNF-band images of AVIRIS images and projected images.

Figure 7. The AVIRIS signatures for some mineral classes and the correspondent projected “signatures” onto the QDIP.
Figure 8. SAM classification results for (a) AVIRIS images and (b) projected images. Different thresholds are used for these two images. (c) & (d) K-means classification results with 11 endmembers for these two groups of images. (e) & (f) Matched filter scores from Zeolites, Calcite and Alunite (2.16) for these two groups of images.
In supervised classification the interpreter should know beforehand what classes are present, where they are in one or more locations within the scene, or what their identical signatures are. Since we have known the signatures for some classes inside the scene, we can project these signatures to the sensor space to get another group of “signatures”, which are shown in Fig. 7 and different detection/classification results are shown in fig. 8.

Table 2 lists the statistics of the above classification results. Classification results from the AVIRIS data are always considered as the ground truth. These results will change with the thresholds used for the classifications, but not much.

<table>
<thead>
<tr>
<th>Classification Method</th>
<th>Overall Accuracy</th>
<th>Kappa Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>IsoData</td>
<td>79.5414%</td>
<td>0.7578</td>
</tr>
<tr>
<td>K-mean</td>
<td>79.5414%</td>
<td>0.7578</td>
</tr>
<tr>
<td>SAM</td>
<td>61.2693%</td>
<td>0.5195</td>
</tr>
<tr>
<td>Minimum Distance</td>
<td>59.1236%</td>
<td>0.4715</td>
</tr>
</tbody>
</table>

Table 2. Confusion matrix statistics results for some classification algorithms.

Notice that MF classification gives almost identical results in these two groups of images while some differences exist in classification results. This is predictable because the number of bias voltages applied to QDIP is selected to be equal to the number of AVIRIS bands and each response of QDIP is interpolated to be a fifty-dimensional vector, then these responses can span the same subspace of the spectral space as the original AVIRIS data. The projected images still lies in the same space and no information is lost in this “projection” process. In fact, the projected images are just the linear transformations of the original images. But it does not mean the classification results are same. While we could precisely predicted the “signatures” in new basis, the criterions for some classifications, like the angles or distances between the vectors, are changed in this scale and they can not be well decided. Only MF or OSP illustrates the identical property for no threshold is needed for this process.

In above simulations, the projected images are the output of the AFPA and the “signatures” for classification can be calculated beforehand. Since “images” are composed of vectors inside the sensor space and the basis are sensor’s responses, they could be electrically achieved by combining different responses with different weights. Operators like MF, OSP and LU could also be fit. Then AFPA perform the correspondent classification at the same time as the measurement process, the sensor output would be the classification result.

For the case of zero noise in this simulation the sensor space is identical with the original AVIRIS space, which is a fifty-dimensional subspace of the spectral space. When noise exists, they are not the same because the noise levels in different bands are usually different. Some QDIP’s bands become so noisy that they are not counted as efficient bands for spectral imagery. From fig.5, we can see the number of efficient bands will drop dramatically with the increase of noise. Generally speaking, sensor with highly correlated responses performs worse than the sensor with uncorrelated responses when noise levels are same.

5. CONCLUSIONS

The main advantage of AFPA is that no optical device is needed before the sensor so that the complexity of the sensor design is greatly reduced. Broadband measurement allows higher intensity of incident light so the SNR of the sensor increase dramatically. In addition, the choice of bias voltages can be altered for particular spectral imaging scenarios. We have examined that AFPA outputs can be the classification result if appropriate operators is built. The best fit comes from the further intuition leading us to an understanding for the spectral imagery that the detector response is also a vector inside the target feature space and different response would build a space so that the output is the projection of target to the space. Then the signature will depend on the sensor type, so does the detection/classification operator.
SVD is then used to uncorrelate the responses and analyze the SNRs for different bands. In this point of view, spectral resolution is not the key factor of the sensor but number of bands. Since the measurement done by sensor is a projection and the post-classification is another projection, it is clear that we can combine them.

The spectral imagery process is an interaction between the ground truth and the sensor. The feature space of the ground truth normally lies in a much lower dimensionality than hyperspectral sensor like AVIRIS, which implies that most of the AVIRIS data are redundant data need to be removed in post-processing. On the other hand, a sensor cannot measure scene composition vectors orthogonal to the sensor space and will lose the information during the measurement, which means too low dimensionality of sensor space limits the imaging ability of the sensor. Adaptive sensing based on QDIP may satisfy both requirements.

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