Guided Filter-Based Medical Hyperspectral Image Restoration and Cell Classification

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Hyperspectral imaging is a newly-developed technique combining imaging and spectroscopy, which has been drawn increasing attention in precise medical diagnostics. The hyperspectral cell data is captured by the system including microscope and hyperspectral camera which promise the data has both high spectral and spatial resolution. In practical imaging process, some spectral bands are inevitably corrupted by noise, making information loss. In this paper, a medical image restoration method based on guided image filter is proposed, which attempts to realize automatic noise suppression and preserve edge of interested targets. The most important step for the proposed method is the choice of guided image, which is selected from original spectral bands with certain criteria. In doing so, the guided image maintains the image physical properties, offering better restoration performance. Furthermore, the restored hyperspectral imagery is employed to classify various kinds of cell targets. Experimental results with several real scenes demonstrate that the proposed method can provide medical images with much better visual effects and higher classification performance.

Keywords: Guided Filter, Band Selection, Spectral-Spatial Features, Hyperspectral Imagery, Cell Classification.

1. INTRODUCTION

Hyperspectral imagery has been initially applied in the area of remote sensing for the space environment exploration and military application. Due to its high spectral resolution, hyperspectral imagery can provide detailed and narrow segmentation in spectral dimension from visible light (VIS) to near infrared (NIR), with reflecting how material particularly absorb and reflect light in the fixed band, containing hundreds of bands that may provide more accurate spectral lines for high discrimination capabilities.1,2 And the new imaging technology makes it possible for both spatial and spectral domain information, where spatial contour of the samples and informative spectral signatures make it easy for classification.

The researchers have obtained a great success on medical data based on machine learning.3–6 Recent years, hyperspectral imagery has been drawn lots of attention in medical sciences, e.g., tongue tumor detection,7 many kinds of cancer detections,8 medical food safety,9 and other diagnostics.10 More higher classification accuracy is provided by wealthy information of medical hyperspectral imagery in application of cell identification. While as an important indicator for maintaining a good healthy, it is necessary for early disease inspection and preservation. Therefore, the high accuracy may really be helpful for medical staffs as an auxiliary method to accurate diagnosis.

Microscopy blood cell inspection is a fundamental tool in basic and applied biomedical research;11–14 for example, the blood routine examination is an important check item to help diagnose the cause of these conditions, including all kinds of cells classification and counting, called complete blood counts, red blood counts and white blood counts. In normal human blood, the number of kinds of cells are absolutely certain per litre, and neither high or low value both indicate that there is something wrong for human body health. In the processing of traditional blood cell inspection, all the above operations are implemented artificially through a microscope which make this process susceptible to man-made errors and time-consuming.15

Microscopic imaging16–18 and computer-aided medical diagnostics19–23 have been widely applied to the medical treatment. In this work, we attempt to employ medical hyperspectral imagery for automatic cell identification. The experimental data is acquired by composing the tunable filters with microscope and silicon charge-coupled devices (CCDs). The framework of cell-capturing system is illustrated in Figure 1. The principle of the system is by the wavelength-scanning, i.e., each single image is transmitted by the light source in the firmed wave bands, and the fast random-access wave-length selection which causes imaging in a simple way. Silicon CCDs are sensitive for a big range of spectral band extending to near infrared, and Silicon CCDs are popularly used in the VIS and NIR regions in medical hyperspectral imaging system.10,24,25 Note that each pixel in the captured scene...
In practical imaging process, some spectral bands are inevitably corrupted by system noise or blurry vision when the camera’s autofocus fails.\textsuperscript{26,27} Recently, the guided image filtering was proposed in Ref. [28], based on a local linear model, which makes it both effective and efficient in image processing. It is popular in detail image enhancement, image fusion and image segmentation.\textsuperscript{29–31} Different from other denoising methods, the ability of preserving edges is provided by this algorithm. In order to avoid the noise and preserve the edge of cells, guided image filter is employed for denoising with band selection which is chosen as the guided image, and then the classic support vector machine (SVM)\textsuperscript{32} is used to automatically classify the red and white cells.

The main contributions of this work are two folds. On one hand, to the best of our knowledge, this is the first time to apply guided image filter for denoising on medical hyperspectral imagery. On the other hand, in the designed system, the guided image, with a description of clear spatial texture, is selected from the original spectral bands, which causes the restored hyperspectral imagery more informative. Furthermore, the restored data is employed to classify various kinds of cells, which is expected to improve the classification performance.

2. IMAGE RESTORATION AND CELL CLASSIFICATION

In order to fully utilize the spectral and spatial information of medical hyperspectral imagery, the proposed classification framework integrates the following steps: guided image chosen with band selection, guided filter-based denoising processing, and the final classification. The aim of band selection is to choose the most appropriate guide image that obtains more effective edge information. There are many methods for dimensionality reduction in hyperspectral image analysis, such as independent component analysis (ICA), principal component analysis (PCA), and Fishers linear discriminant analysis (LDA). Above methods can be divided into the category of matrix-projection. An alternative dimensionality reduction is band selection, which is to find a set of distinctive and informative bands in the imagery,\textsuperscript{33} while in
Fig. 4. Illustration the difference between spectral signatures of some randomly-selected pixels for red cells and white cells, (a) five spectral lines, and (b) the averaged spectral lines for the VIS dataset I.

In this paper, we just need to choose one, but the most optimal band for a guidance. The difference is that the former may change the structure of original data, while the latter focuses on the physical meaning from the original bands. In our work, we choose band selection for maintaining initial properties (the value of transmittance for various bands in the imaging process) rather than other methods through matrix-projection transform. Once obtained the guided image, guided filter is employed for denoising, followed by a classification task. The flowchart of the proposed framework is illustrated in Figure 3.

2.1. Guided Image Chosen via Band Selection

A guided image is chosen with band selection for the following denoising process by guided filter. Medical hyperspectral imagery contains dozens of spectral bands that are highly correlative. The guided image, expected to provide a description of clear spatial texture, will be selected from the original spectral bands.

As known, the typical PCA seeks to find a linear transformation which projects the data from a high-dimensional space into a lower dimensional subspace by maximizing the variance of the data in the projected subspace. The first principal component (PC1) maintains most of the energy with less noise. Thus, in our method, we employ the PC1 as benchmark to select the as far as possible informative band from the original spectral cube. In this work, a criterion of linear prediction error (LPE) is employed during the process of band selection. The LPE weighs the diversities among all the spectral bands through linear projections with the PC1, and a prediction error is calculated between them. After that, the band with minimum error will be selected as the guided image.

Assume that $\mathbf{y} \in \mathbb{R}^{m \times n}$ represents the PC1 and $\mathbf{X} = \{\mathbf{x}_i\}_{i=1}^d \in \mathbb{R}^{m \times n \times d}$ is the original hyperspectral cube. Note that $m \times n$ represents the spatial image size and $d$ is the number of spectral bands. The prediction process can be described as,

$$y_i = \mathbf{x}_i (\mathbf{x}_i^T \mathbf{x}_i)^{-1} \mathbf{x}_i^T \mathbf{y}$$

(1)

where $y_i$ is the approximation for $i$-band $\mathbf{x}_i$. And then, the prediction error $e_i = \|y_i - \mathbf{y}_i\|_2$, and the minimum value of $\{e_1, e_2, \ldots, e_d\}$ determines the final selected band (as the guided image). The overall description of the guided image selection is given as Algorithm 1.

**Algorithm 1 (Guided Image Chosen via Band Selection).**

**Input:** Hyperspectral cube $\mathbf{X} = \{\mathbf{x}_i\}_{i=1}^d$.

Employ the PCA on $\mathbf{X}$ to obtain the PC1;

Calculate prediction via solving Eq. (1) in a closed form;

Compute prediction error for all the bands;

**Output:** Selected band with minimum prediction error.

It is apparent that the proposed method of guided image selection has simple computational complexity. That is, the criterion of prediction error estimation is with a closed form; furthermore, the minimum error can be decided using only one ergodic for all the bands. In fact, the PC1 itself can be also viewed as the
guided image while the method changes the physical meaning of the original data. In the experimental section, these two choices of guided image (i.e., the PC1 and the one obtained by band selection) will be discussed.

2.2. Guided Filter-Based Denoising

Let $X^0$ represents the original image, $X^R$ represents the recovered image, and $X^G$ represents the guided image. Guided filter, as a local edge-preserving filter, is a filtering process using a local window with a radius $r$. The restoration process can be a local linear representation of the guided image as following,

$$X^R = a_iX^G + b_j$$

(2)

where $(a_j, b_j)$ are constant terms for the linear representation in a local window $\omega_j$ centered at the pixel $j$, index $i \in \omega_j$. $X^R$ and $X^G$ represent one pixel within the region $\omega_j$ of $X_R$ and $X_G$. This local linear model assures that the restoration image will have an edge of guided image because of linear relation. The determination of linear coefficients is solved by minimizing the objective function,

$$E = \sum_{i \in \omega_j}((a_iX^G + b_j - X^0_i)^2 + \varepsilon a_i^2)$$

(3)

where the regularization parameter $\varepsilon$ is used to adjust and avoid the linear coefficients too large. According to the cost function, it is expected that the recovered image $X^R$ is as far as possible similar to $X^0$, for preserving more detailed information through the linear model to obtain the texture information from $X^G$. Note that the linear coefficients subsequently equal to,

$$a_j = \frac{(1/|\omega|)\sum_{i \in \omega_j}X^G_iX^0_i - \mu_j \bar{X}^0_j}{\sigma_j^2 + \varepsilon}$$

(4)

and

$$b_j = \bar{X}^0_j - a_j \mu_j$$

(5)

where $\mu_j$ and $\sigma_j^2$ are values of mean and variance within the region $\omega_j$ of $X^G$. $|\omega|$ means the number of pixels within the local window $\omega_j$ with radius $r$ centered at the pixel $j$, and $\bar{X}^0_j$ represents the average value of input image within the local region.

For each pixel, the final value of restoration image is calculated by averaging in the whole image,

$$X^R = \frac{1}{|\omega|} \sum_{i, j \in \omega_j} (a_jX^G_i + b_j) = \bar{a}_jX^G_i + \bar{b}_j$$

(6)

where $\bar{a}_j = (1/|\omega|)\sum_{i \in \omega_j} a_j$, and $\bar{b}_j = (1/|\omega|)\sum_{i \in \omega_j} b_j$. It is worth noting that this averaging strategy of overlapping has been popularly employed in the image denoising. After the medical hyperspectral imagery is restored, a typical SVM classifier is employed for the following classification task.

3. EXPERIMENTS AND ANALYSIS

In this section, we mainly investigate the restoration performance using guided filter, including discussion about the choice of guided image while the method changes the physical meaning of the original data. In the experimental section, these two choices of guided image (i.e., the PC1 and the one obtained by band selection) will be discussed.
of guided image, and the classification performance with comparison with some state-of-the-art techniques. All experiments are carried out using Matlab on an Intel i7 quad core 3.60-GHz machine with 16 GB of RAM.

3.1. Data Analysis
The first experimental dataset is collected by composing the VariSpec Liquid Crystal Tunable Filters (LCTFs) with microscope and silicon charge-coupled devices (CCDs). The data wavelength is in the range of visible-wavelength (VIS), from 400 nm to 720 nm, following 10 nm as an imaging step size, and totally acquiring all 33 bands for completing the imaging process. The original image includes $973 \times 799 \times 33$ and we resize the data into $200 \times 200 \times 33$ as our first experimental data (denoted as VIS I). We randomly select 5 different pixels of two types of cells (i.e., red cells and white cells) as shown in Figure 4(a) and the averaging spectral lines as shown in Figure 4(b). Each pixel in the hyperspectral images has a brightness of the discontinuous

![Restoration illustration for VIS I data](image1)

Fig. 10. Restoration illustration for VIS I data, (a) original image (OI) band (7th), and (b) recovered images with various parameters of guided image filter.

![Parameter tuning process for the guided image filter with classification for datasets](image2)

Fig. 11. Parameter tuning process for the guided image filter with classification for datasets, (a) VIS I, and (b) NIR.

![Classification performance comparison of the typical SVM classifier with and without filtering](image3)

Fig. 12. Classification performance comparison of the typical SVM classifier with and without filtering, (a) VIS I, and (b) NIR.
changes for various wavelength, while pixels from the same class have similar spectral structure. In Figure 4(b), we further observe that the spectral curves of two types of cells are distinctive, which provides potential probability to separate them even in complex scenario. In our experiments, there are three classes, including background, white cells and red cells, and the ground truth map is shown in Figure 5(b), where yellow color represents the region of white cells, purple color indicates the one of red cells, and others are background. Figure 5(a) illustrates a synthetic pseudo-color image from selected 3 bands, from which it is actually not easy to visually recognize these three classes (the black circles indicates the region of white cells).

After testing with this smaller size data, we will evaluate all the methods using the data with original image size, i.e., 973 × 799 × 33, which is viewed as our second dataset (denoted as VIS II). Here, note that acquired by the same device, larger white cell region is included. Figures 6(a) and (b) illustrate the synthetic pseudo-color image and the ground truth map.

The third experimental dataset is acquired by the Acousto-optical tunable filter (AOTF) and CCDs, and captured images from 550–1000 nm including the part of near-infrared wavelength for all 40 bands, and the spectral resolution is 2–5 nm. We resize the data as 350 × 350 × 40 in our following experiments. There are also three classes, including the background, white cells, and red cells, related pseudo-color image and ground truth map are illustrated in Figures 7(a) and (b).

3.2. Parameters Tuning

The ground truth map is separated into training set and testing set. In our experimental setting, there are 50 samples randomly selected training set per class from the ground truth
map. The parameter tuning process has been tested further more divided training set into the training samples and testing samples (all the chosen parameters are based on the training set), aiming to produce optimal classification performance. For guided image filter, the most important step is to choose an appropriate guided image. Figures 8(a) and (b) illustrate the prediction error between approximation and the PC1 as a function of number of bands for two datasets. According to the designed criterion, the one with minimum prediction error determines the index of band (i.e., respectively for 13 and 1), which is selected as the guided image. Figure 9 further provides visual comparison of two choices of the guided image. Figure 9(a) illustrates the PC1 calculated based on

Fig. 15. Classification maps with (a) original image (OI) bands, (b) MF, (c) WF, (d) K-SVD, (e) GF_PC, and (f) GF BS for VIS dataset I.

Fig. 16. Classification maps with (a) original image (OI) bands, (b) MF, (c) WF, (d) K-SVD, (e) GF_PC, and (f) GF BS for VIS dataset II.
the first experimental data, and Figure 9(b) shows the one determined by band selection. After projected by PCA transform, the PC1 contains the most significant amounts of energy; however, it has an issue of fusion edges as shown in the highlighted two regions (marked by two red rectangles). Comparatively, the one as shown in Figure 9(b) provides more clear texture information, especially on the edges. Thus, it is expected that the restoration performance is more competitive when using the guided image determined by band selection.

Parameters $r$ and $\varepsilon$ play important roles in the guided image filter. Take the first experimental data for example, Figure 10 illustrates the restoration performance of several recovered images using various parameters. It is clear to observe that when parameters $r$ and $\varepsilon$ change, the recovered images have obviously different quality. Furthermore, Figures 11(a) and (b) show the classification performance with a wide range of $r = \{5, 10, 15, 20, 25, 30, 40\}$ and $\varepsilon = \{1e - 2, 1e - 1, 1, 5, 10, 15, 20\}$ for the VIS dataset I, then $r = \{1, 3, 5, 7, 9\}$ and $\varepsilon = \{1e - 2, 1e - 1, 1, 5, 10\}$ for the NIR dataset. Note that we use the same parameters of VIS I for the VIS II dataset.

In our following experiments, we choose the best parameters of $r = 30$ and $\varepsilon = 10$ for both VIS datasets and $r = 3$ and $\varepsilon = 1e - 1$ for the NIR dataset. As for parameter tuning of the typical SVM classifier, Figure 12 shows the classification performance with a region of $\sigma^2 = \{1e - 4, 1e - 3, 1e - 2, 1e - 1, 1, 10, 100\}$ with and without filter respectively for two datasets. On one hand, the optimal parameter is decided with $\sigma^2 = 1e - 1$ in VIS I and II, and $\sigma^2 = 1e - 3$ for without filtering, while $\sigma^2 = 1e - 2$ for with filtering when using NIR data. On the other hand, it is clear to observe that the typical SVM with filter provides consistent improvement compared to the one without filter, which indicates the benefit of the guided image filter.

### 3.3. Classification Performance

According to previous analysis, for the VIS data, the 13th spectral band is viewed as the guided image. The first original image (OI) band (7th) and recovered images by different restoration methods are illustrated in Figure 13, while the third original image (OI) band (2nd) and the same methods for restoration in Figure 14. Among these methods, mean filter (MF), wavelet filter (WF), the state-of-the-art K-SVD,37 and the proposed guided filter (GF) are implemented with optimal parameters; for example, slide window of the MF is chosen with the size of 5 × 5. For comparison, we employ the PC1 as guided image for GF, denoted as GF_PC, and the one determined by band selection, denoted as GF_BS. Also, GF_PC has the similar parameter tuning with GF_BS.

Figure 13 illustrates the restoration performance of aforementioned methods. Note that the 7th spectral band is noisy, and the texture and edges are seriously damp. The MF can improve the situation while little noise still exists in Figure 13(b); the WF and K-SVD provide recovered images with less noise but edges are blurred in Figures 13(c) and (d). Figures 13(e) and (f) are better than others for visual illustration, and Figure 13(f) has obviously clear edges and the best performance, which verifies the effectiveness of the proposed filter.

On account of the guided filter with a nature of maintaining the texture and edge information from guided image,

### Table I. Overall Accuracy (OA%) of some comparison methods for three experimental datasets.

<table>
<thead>
<tr>
<th>Processing (%)</th>
<th>OI</th>
<th>MF</th>
<th>WF</th>
<th>K-SVD</th>
<th>GF_PC</th>
<th>GF_BS</th>
</tr>
</thead>
<tbody>
<tr>
<td>OA_VIS I</td>
<td>92.19</td>
<td>93.79</td>
<td>92.27</td>
<td>93.19</td>
<td>94.53</td>
<td>96.80</td>
</tr>
<tr>
<td>OA_VIS II</td>
<td>83.22</td>
<td>90.10</td>
<td>90.57</td>
<td>86.91</td>
<td>92.60</td>
<td>93.23</td>
</tr>
<tr>
<td>OA_NIR</td>
<td>92.22</td>
<td>94.72</td>
<td>92.84</td>
<td>96.33</td>
<td>96.44</td>
<td>96.47</td>
</tr>
</tbody>
</table>

Fig. 17. Classification maps with (a) original image (OI) bands, (b) MF, (c) WF, (d) K-SVD, (e) GF_PC, and (f) GF_BS for NIR dataset.
Table II. Confusion matrix and true positive rate (TPR) of GF_BS for three experimental datasets.

<table>
<thead>
<tr>
<th></th>
<th>VIS I</th>
<th></th>
<th>VIS II</th>
<th></th>
<th>NIR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>TPR (%)</td>
<td>24324</td>
<td>591444</td>
<td>48871</td>
<td>207</td>
<td>12745</td>
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<tr>
<td></td>
<td>564</td>
<td>17462</td>
<td>5129</td>
<td>365</td>
<td>230405</td>
</tr>
<tr>
<td></td>
<td>88.85</td>
<td>97.77</td>
<td>97.77</td>
<td>91.45</td>
<td>91.45</td>
</tr>
</tbody>
</table>

Table III. Computational cost (in Second) of the proposed guided image filter of three experimental datasets.

<table>
<thead>
<tr>
<th>Window size (time/s)</th>
<th>5</th>
<th>10</th>
<th>15</th>
<th>20</th>
<th>25</th>
<th>30</th>
<th>40</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIS I_GF</td>
<td>0.13</td>
<td>0.13</td>
<td>0.13</td>
<td>0.13</td>
<td>0.13</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>VIS II_GF</td>
<td>6.11</td>
<td>5.79</td>
<td>5.74</td>
<td>5.73</td>
<td>5.72</td>
<td>5.72</td>
<td>5.72</td>
</tr>
<tr>
<td>NIR_GF</td>
<td>0.55</td>
<td>0.55</td>
<td>0.66</td>
<td>0.66</td>
<td>0.66</td>
<td>0.54</td>
<td>0.52</td>
</tr>
</tbody>
</table>

the classification performance has been further compared. Figures 15–17 illustrate the classification maps using original image (OI) data as well as aforementioned methods. Without any spatial preprocessing, it is clearly to observe that the maps in Figures 15(a)–17(a) are noisy. The reason is that only using spectral features does not fully utilize the fact that neighboring pixels in hyperspectral imagery have high probability to belong to the same class.

In Figures 15(b)–(e) for the VIS I data, these methods are relatively robust in the influence of noise; nevertheless, region of few red cells is still recognized as that of white cells. The proposed GF_BS has the best performance among these methods. As for the NIR dataset, the K-SVD gets the similar performance with the methods of owning guidance information, but it has a high cost of time and cannot preserve the edge of cells; furthermore, the choice of guidance image seems to be more effective when the edges are fuzzy, and we observe that for the NIR dataset, there are few fuzzy edges than the first dataset. Tables I and II further list the overall classification accuracy (%) and confusion matrix. The proposed GF_BS provides 96.80% accuracy, resulting in an improvement of approximately 3% compared to the state-of-the-art K-SVD and 2% compared to the GF_PC for the first experiment data. For another two datasets, the proposed method also displays the importance of classification accuracy and visual effects.

Table III further lists the computational time (in Second) for the proposed method when various window size is used. It turns out that the proposed method has little complexity cost and does not change much even when the window size is large (e.g., 40).

Hence, we conclude that the proposed classification framework is a very effective strategy from the perspective of restoration, classification, and computational complexity for medical hyperspectral image analysis.

4. CONCLUSIONS

In this paper, a medical hyperspectral image analysis system for human blood cell recognition has been designed, improving the capacity of distinguishing white cells and red cells. The motivation of doing this work is due to the fact that the quality of collected microscopic hyperspectral image dataset, usually corrupted by system noise, has serious effect on the classification performance. In the proposed method, a guided image, chosen via band selection with certain criterion, was used for hyperspectral cube restoration with guided image filter. Experimental results demonstrated that the recovered images have provided better visual performance compared to several traditional methods. Based on the restoration data, the proposed method could identify different types of cells at a higher recognition rate (with an improvement of approximately 4% for both VIS and NIR experimental datasets when compared to the original image bands), indicating a higher reliability in medical diagnosis.

The stability and definition of feasible system still need to further search for more details. In our future, more sophisticated blood-cell classification will be investigated. We would like to establish a cell bank, for automatically identifying normal and diseased cells, including several different types of white cells.

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References and Notes


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