Iterative Graph-Based Filtering for Image Abstraction and Stylization

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***Abstract*—In this brief, motivated by the recent advances in graph signal processing, we address the problem of image abstraction and stylization. A novel unified graph-based multi-layer framework is proposed to perform iterative filtering without requiring any weight updates. The proposed graph-based filtering approach is shown to be superior to other existing methods due to iteratively using the filtered Laplacian in order to enhance the smoothened image signal at each layer. In order to render real images into painterly style ones and create a simple stylized format from color images, the low-contrast regions of an image are first smoothened using the proposed iterative graph filters in either vertex or spectral domains. The abstracted image is then quantized and sharpened using the proposed iterative high-pass graph filter. The effectiveness of the graph-based image stylization method is verified through several experiments. It is shown that the proposed method can yield significantly improved visual quality for stylized images as compared to other existing methods.**

***Index Terms*—Iterative graph filtering, spectral filtering, signal processing, abstraction, stylization.**

I. Introduction

In this age of big data, we need to revisit traditional signal processing solutions and extend their applicability to emerging problems with large data sets. In such applications, the critical problem is that typically rendering classical signal processing solutions may be incapable of properly handling big data problems which are of great engineering importance. Recently, graph signal processing [1]–[3] has provided a new framework for representing model relations among data samples. For data-oriented applications [3], a weighted graph can be identified to capture similarities between data samples. For instance, an image may be represented by associating image pixels with graph nodes. The corresponding graph can be analyzed using newly-defined signal processing techniques [1].

Leveraging the new framework of graph signal processing, we address the problem of image stylization, i.e., synthesizing an artistic cartoon/painterly-like image from a new point of view. In recent years, stylized images in the computer graphics, artistic works, social networks, and entertainment have received considerable attention [4]. Image abstraction is an image processing problem used to modify the contrast of visually important features in order to stylize and create cartoon-like effects on images [5]–[7]. In [5], a l_0 gradient minimization method has been proposed for image editing by optimizing a global function to control the non-zero gradients. In [6], a scale-aware rolling guidance filter (RGF) has been proposed for detail smoothening in the context of iterative joint bilateral filter. In [7], a graph-based structure-preserving filter has been proposed for smoothening high-contrast details by constructing a minimum spanning tree between image patches.

Image stylization has a wide range of applications, including allowing for artistic data-driven simulations of ink, watercolor, oil paintings and cartoons [8]–[10]. Particularly, a framework for synthesizing non-photorealistic animatory styles such as painterly, sketchy, and cartoon-like shadings from real videos has been proposed in [11]. A line-drawing approach has been proposed for the purpose of image stylization in [12], where the Canny edge detector and mean-shift filter have been successively combined to obtain a cartoon-style image. Data-driven stylization and abstraction methods for portrait sketch synthesis have been proposed in [13] by analyzing both the characteristics of the strokes and the differences between the shape of the faces and reference images. In [14], an extension to the difference of Gaussian operator for edge detection has been proposed. It has been shown in [14] that this new extension is promising for producing variety of styles such as pencil-shading, pastel and woodcut. In [15], a direction-enhancing edge flow field has been proposed for line drawing. It has been shown in [15] that this technique can preserve edge localization and offer additional features for creating hand-painting style images. While a variety of approaches exist for abstracting images and stylizing them, they fall short in providing unified multi-layer abstraction and stylization methods which can be generalizable to large video sequences.

In view of this, in this brief, a new unified multi-layer framework for parallelized lowpass and highpass filtering is proposed. The proposed filtering framework is capable of simultaneously manipulating and enhancing fine details in the image. Therefore, a preprocessing stage to remove distortions in the image is not needed leading to significant computational savings. The proposed methodologies are realized by applying a sequential filter comprising the detail removal and sharpening stages. For detail removal, two graph filters one in the vertex domain and the other one in the spectral domain are proposed to reduce the contrast in low-contrast regions. To this end, we make use of the graph Laplacian matrix obtained from the similarity matrix to enhance the smoothened output of each layer. In contrast to other multi-scale detail

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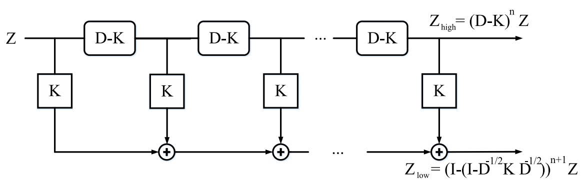

Fig. 1. Proposed graph-based iterative filtering for image abstraction.

decomposition schemes, the proposed graph-based multi-layer filtering framework does not require weight updating at each layer, since the weights are computed once and used in the following computations. This strategy not only reduces the computational complexity of the algorithm but also enables efficient spectral analysis of the filters. To obtain stylistic illustrations from color images, the abstracted image is quantized and contrast in high-contrast regions is increased by iteratively adding a highpass graph filtered version of the image to its quantized version. Simulation results evaluate the effectiveness of the proposed graph-based method in image abstraction and stylization and include comparisons with other existing works.

II. Graph Construction

Graph signal processing is an emerging field that offers a framework for applying classical signal processing to large data sets by defining signals on graphs [2]. Let image z be defined as an intensity function on the vertices V of a weighted graph $G = (V, E, K)$ consisting of a finite set V of vertices (image pixels) and a finite set E of edges with the corresponding weights $k_{pq} \in K$, denoting similarity between vertices (pixels) p and q in the graph. The similarity weights of size $m \times m$ are represented as $K = [k_{pq}]$, where k_{pq} is defined as follows

$$k_{pq} = \exp\left(-\left[\frac{d_c^2}{2\sigma_c^2} + \frac{d_g^2}{2\sigma_g^2}\right]\right), \tag{1}$$

where $d_c = \sqrt{(L_p - L_q)^2 + (a_p - a_q)^2 + (b_p - b_q)^2}$ is the color distance, $d_g = \sqrt{(x_p - x_q)^2 + (y_p - y_q)^2}$ is the geometrical distance, σ_c and σ_g control the level of smoothening achieved by (1), x and y denote the pixel position in the image, L is an intensity measurement, and finally a and b represent the color components [16]. The graph Laplacian matrix is derived from K and plays an important role in describing the underlying structure of the graph signal. The graph combinatorial and normalized Laplacian matrices are defined as $L = D - K$ and $Ł = I - D^{-1/2}KD^{-1/2}$ [17], respectively, where I is the identity matrix and $D = \mathrm{diag}\{\sum_q k(1, q), \ldots, \sum_q k(m, q)\}$.

Spectral graph theory studies the graph properties in terms of eigenvalues and eigenvectors associated with the adjacency or Laplacian matrices of the graph. Term Ł is a real symmetric matrix, thus is diagonalizable to its eigenbasis as given by $Ł = \sum_i \lambda_i u_i u_i^T$, where $\lambda = \{\lambda_i\}_{i=1,\ldots,m}$ is the set of eigenvalues and $U = \{u_i\}_{i=1,\ldots,m}$ the set of orthogonal eigenvectors. Set U constitutes the basis function for the underlying signal defined on graph, and λ is known as the corresponding graph frequencies. The graph Fourier transform $\tilde{z}$ of a signal z is therefore defined as $\tilde{z} = U^T z$ [1]. In the next section, we present a new multi-layer graph-based filtering approach used for image abstraction and stylization.

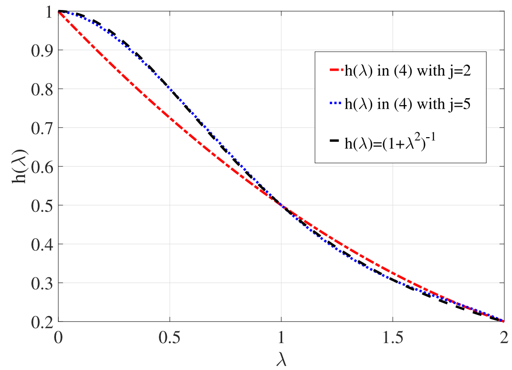

Fig. 2. Spectral response $h(\lambda)$ of the proposed graph-based filtering in the spectral domain with different polynomial degrees.

III. Image Abstraction

The proposed image abstraction and stylization methods are realized by applying a progressive filtering process consisting of smoothening and sharpening filters. The first stage smoothens the image by utilizing graph-based filters in the vertex and spectral domains.

A. Vertex Domain Filtering

In order to smoothen an image, in this brief, we propose a graph-based filtering method to reduce contrast in low-contrast regions and to eliminate fine structures such as weak edges and possible noise. For signals defined on graphs, filtering can be done in both the vertex and spectral domains similar to the procedure followed in conventional signal processing methodologies. In the vertex domain, a graph signal z can be iteratively filtered in a multi-layer manner, as shown in Fig. 1, using the following expression

$$z_f = I - \left(I - D^{-1/2}KD^{-1/2}\right)^{n+1} z, \tag{2}$$

where n is the iteration index and z_f is the filtered version of z. With the use of the proposed iterative graph filtering, the weaker edges are removed while the stronger ones are preserved. Using the proposed filter in (2), we can obtain a multi-layer abstracted image by utilizing only the similarity matrix K of the original image. It is to be pointed out that the proposed data-dependent filtering method iteratively uses the graph Laplacian matrix to enhance the filtered version of the signal at each layer, since it contains some of the underlying signal structure. Abstracted images are useful in several applications such as saliency/object detection and retargeting.

B. Spectral Domain Filtering

It is known that the graph spectral domain provides sparse representation of the graph signals which may be desirable in many applications [1]. In view of this, we further investigate the possibility of an alternative to the proposed graph vertex-domain filter in the graph spectral domain. To this end, the graph Laplacian matrix is decomposed into its eigenvalues and eigenvectors and the corresponding spectral filter is designed. The signal can be filtered in the spectral domain as

$$\tilde{z}_f = h(\lambda)\tilde{z}, \text{ with } \tilde{z} = \sum_i u_i z \tag{3}$$

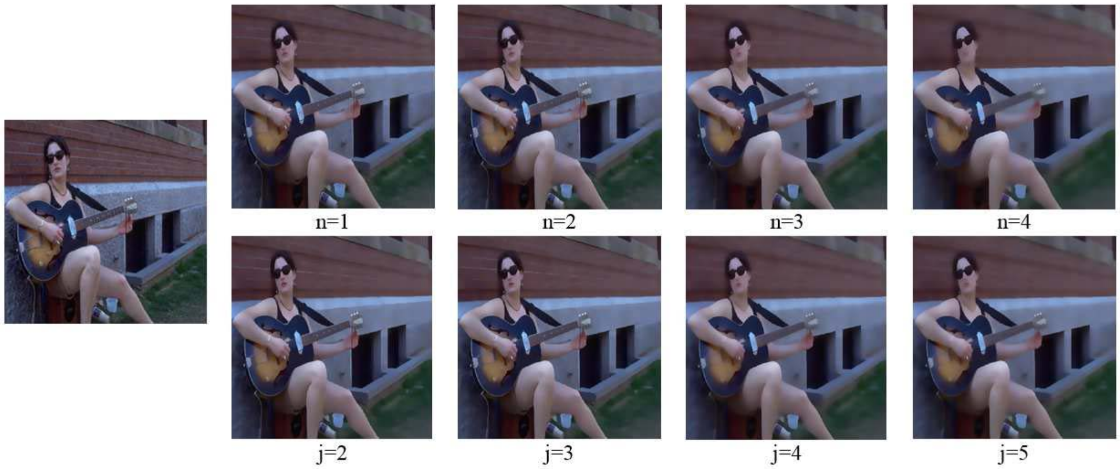

Fig. 3. Proposed iterative graph-based detail removal filtering. Original *Margaret* image with synthetic noise as well as its abstracted versions using the vertex domain filter in (2) with various iteration index n values and using the spectral domain filter in (3) and (4) with different polynomial degrees j.

being the projected signal onto the graph Fourier domain and

$$h(\lambda) = \sum_{0 \le i \le j} l_i \lambda^i \tag{4}$$

is the filter spectral response representing the Lagrange interpolation polynomial expressed as a function of λ with degree j, which is an approximated version of $h(\lambda) = (1+\lambda^2)^{-1}$ [18]. The approximated filter spectral response in (4) for a general case of Laplacian can be derived as

$$\left| h(\lambda)\tilde{z} - \sum_{0 \le i \le j} l_i \lambda^i \tilde{z} \right| \le \epsilon, \tag{5}$$

in which ϵ can be upper-bounded by

$$\underbrace{\max}_{[\lambda_{min},\lambda_{max}]} |\epsilon| \le \frac{\max\left|h^{(j+1)}(\lambda)\right|}{(j+1)!} \max\left|w_{j+1}(\lambda)\right|, \tag{6}$$

where $w_{j+1}(\lambda) = \prod_i (\lambda - \lambda_i)$. The filtered signal $\tilde{z}_f$ in the spectral domain can be regarded as a linear combination of the components of the input signal within a j-hop local neighborhood. For instance, the filter spectral response for a polynomial of degree $j = 2$ can be obtained as $h(\lambda) = I - 0.6\lambda + 0.1\lambda^2$, knowing that the graph frequencies of the normalized Laplacian matrix Ł are within the interval [0, 2] [1]. This filter leaves the high-contrast edges unaltered, while it has a strong smoothing effect on more homogeneous regions. Fig. 2 shows the spectral response of the approximated filters with different polynomial degrees. It is seen from this figure that using (4) with $j = 5$, we can have a good approximation of $h(\lambda)$. It should be noted that both the proposed filters in the vertex and spectral domains can be interchangeably used for abstracting images. The resulting abstracted image is used in the next section for stylization purpose.

IV. Image Stylization

The output of the proposed image abstraction method can be further processed to obtain stylized cartoon/painterly-like images. For this purpose, we first perform quantization on the luminance channel of the abstracted image as is given by $\hat{z}_f = \Lambda(\lfloor \frac{z_f}{\Lambda} + 1 \rfloor)$, where $\hat{z}_f$ and z_f are the abstracted image and its quantized version, respectively, $\Lambda(.)$ is the quantization step and $\lfloor . \rfloor$ denotes the floor operator. The quantization operator can be adaptive and image-dependent. However, in order to have a unified stylization method, we consider a fixed quantization step independent of the underlying image.

Sharpening is a process used for boosting images with high pass filtering, i.e., amplifying high frequency details in images. Since boosting details in the original image may also result in noise amplification, one needs to first smoothen the image and remove the noise and low-contrast details as much as possible as discussed in Section III-A. In addition to noise, other high contrast artifacts in color images such as false color artifacts should be precluded. To this end, we convert the original RGB color image to *Lab* color space since this color space is uniform and more similar to the human perception. In order to further reduce the false color artifacts in color channels, a smaller value of the sharpening parameter γ for the color channels should be selected. In order to increase contrast in higher contrast regions, edge detection techniques based on Canny, Laplacian of Gaussian and difference of Gaussian [14] detectors have been widely deployed. The resulting edge maps have been used in the context of a shock filter [19] to highlight edges with large magnitude. In this brief, in order to boost the high-contrast regions of the image, we propose the use of iterative graph filtering as is shown in Fig. 1 and given by

$$z_{\rm sh} = h_{\rm sh}(L)z = \left(I + \gamma L^n\right)z = \left(I + \gamma (D-K)^n\right)z, \tag{7}$$

where $z_{\rm sh}$ is the sharpened version of z and the sharpening parameter γ controls the level of contrast enhancement in the output image. The more the value of γ is, the more the detail enhancement level of the filter increases. The sharpening filter in (7) can be regarded as iteratively adding a highpass-filtered version of each channel to the abstracted ones. Correspondingly, the spectral response of the proposed iterative sharpening filter $h_{\rm sh}(\lambda)$ obtained using the graph normalized Laplacian matrix is given by $h_{\rm sh}(\lambda) = (I + \gamma\lambda^n)$.

V. Simulation Results

We conduct experiments on a set of color images to evaluate the performance of the proposed image abstraction and

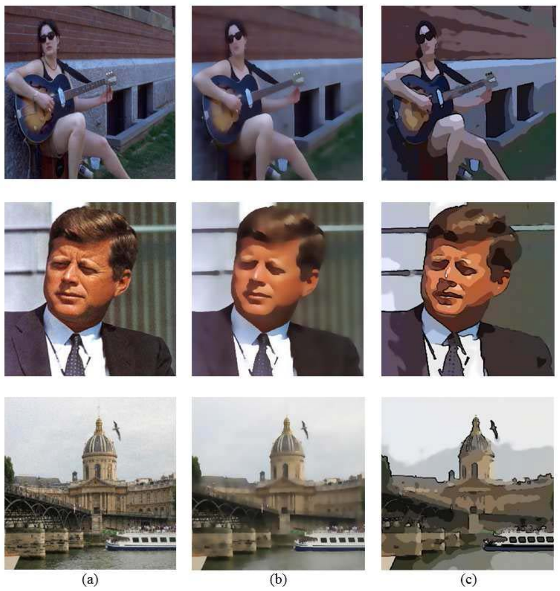

Fig. 4. Proposed graph-based image abstraction and stylization method. (a) Original, (b) abstracted using (2) with $n = 3$, and (c) stylized images.

stylization method. Due to space constraint, only results from some of the test images are reported here. The RGB color images are first converted to the *Lab* color space. A similarity matrix K for the color channels is first constructed. In our simulations, the quantization step Λ is considered to be constant and set to 15. The sharpening parameter γ is set to 1.3 for the luminance and 0.2 for the color channels. We first consider the image abstraction problem and use the filters in (2) and (3) to obtain the abstracted images. Fig. 3 illustrates the original *Margaret* image contaminated by an additive Gaussian noise with noise standard deviation $\sigma_\eta = 0.1$, as well as its abstracted version obtained using the proposed iterative graph-based filters in (2) with different iteration indexes n and, in (5) with different polynomial degrees j. It is seen from this figure that the proposed iterative graph filter in both the vertex and spectral domains are very well capable of smoothening the image by removing fine details while preserving the high-contrast edges. It is also observed from this figure that by increasing n, the image is iteratively filtered. Depending on the application, one can set n to a specific value. For the proposed image stylization method, we set $n = 3$. It is experimentally found that the spectral domain graph filter in (3) can be well approximated by a polynomial of degree $j = 5$. Fig. 4 shows the original images *JFK* with inherent noise, *Academy* and *Margaret* with synthetic noise as well as their corresponding abstracted (using (2) with $n = 3$) and stylized images obtained using the proposed graph-based filtering method. It can be seen from this figure that the proposed method provides cartoon and painterly-like images by taking advantage of iterative graph-based filtering.

We now compare the proposed filtering output with those of the l_0 gradient minimization approach [5] and RGF [6]. Figs. 5 and 6 show the original *Rug* and *Flower* images as well as their smoothened versions obtained using the proposed graph-based method and the corresponding ones yielded by [5] and [6]. It can be seen from these figures that the proposed iterative graph-based filter can perform better smoothening by removing more details as compared to [5] and [6], resulting in smoothened images with sharper edges and more resolution contrast. This is clearly noticeable, especially from the edges highlighted by black arrows and the surrounding areas. This improvement can be attributed to iteratively employing the residuals (differences of smoothened images) in the context of the graph Laplacian matrix used in the filtering process. Next, we compare the performance of the proposed image stylization method using graph-based filtering to those of other existing methods, namely, RGF [6], unsharp masking, shock filter [19] and difference of Gaussian-based

Fig. 5. Image smoothening comparison. (a) Original *Rug* image and smoothened versions obtained using (b) [5], (c) [6], and (d) the proposed method.

Fig. 6. Image smoothening comparison. (a) Original *Flower* image and smoothened versions obtained using (b) [5], (c) [6], and (d) the proposed method.

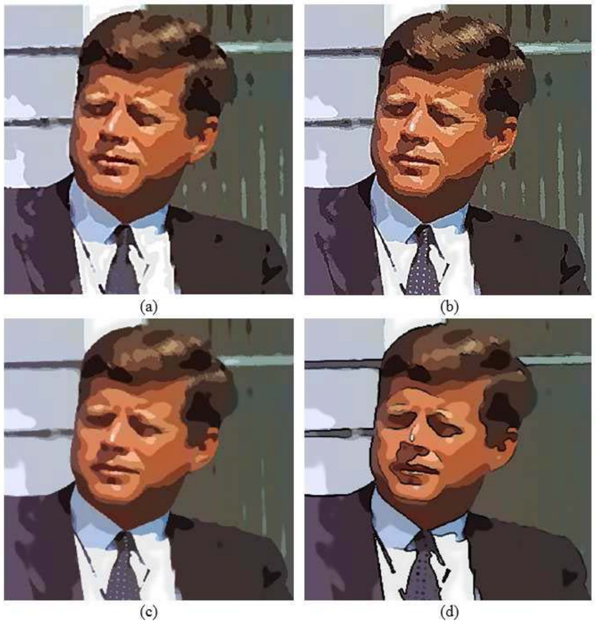

Fig. 7. Comparison of stylized *JFK* image obtained using (a) shock filter, (b) unsharp masking, (c) difference of Gaussian and (d) the proposed method.

Fig. 8. Comparison of stylized images obtained using the proposed method (down) and RGF [6] (up).

image stylization [14]. For the case of difference of Gaussian edge detection, we use our graph-based detail removal method for image abstraction. Figs. 7 and 8 illustrate the stylized images obtained using the aforementioned approaches. It can be observed from Fig. 7 that our proposed image stylization method is superior to other approaches in terms of providing cartoon-like images with no horizontal or vertical artifacts and creates smooth and coherent transitions along line and curved boundaries. In comparison to the recent algorithm in [6], Fig. 8 corroborates our earlier observations of our image stylization approach by providing sharper edges and less artifact in the stylized images.

VI. Conclusion

In this brief, we have proposed a novel and efficient method for image abstraction and stylization. The proposed method has been developed using a new unified iterative graph-based filtering framework based on the graph similarity and Laplacian matrices without requiring any weight updates. The proposed image abstraction method is composed of iterative filtering for detail removal and region smoothening followed by the luminance channel quantization to stylize an image with paint or cartoon-like effects and edge sharpening. By applying the proposed sequential filter to the original image, stylization effect has been generated in the output image. The results have shown that the proposed method can produce multi-layer abstracted images while retaining much of the perceptually important information. The improved performance can be attributed to the use of graph Laplacian to iteratively enhance the smoothened image. The resulting stylized images are shown to be visually more pleasant than those produced by the other methods. Among possible applications, the proposed abstraction method can be utilized for saliency detection, retargeting and painterly-style video production.

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