PEER GROUP FILTERING AND PERCEPTUAL COLOR IMAGE QUANTIZATION

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ABSTRACT

In the first part of this work, peer group filtering (PGF), a nonlinear algorithm for image smoothing and impulse noise removal in color images is presented. The algorithm replaces each image pixel with the weighted average of its peer group members, which are classified based on the color similarity of the neighboring pixels. Results show that it effectively removes the noise and smooths the color images without blurring edges and details. In the second part of the work, PGF is used as a preprocessing step for color quantization. Local statistics obtained after PGF are used as weights in the quantization to suppress color clusters in detailed regions, since human perception is less sensitive to the differences in these areas. As a result, very coarse quantization can be obtained while preserving the color information in the original images. This can be useful in color image segmentation and color image retrieval applications.

1. INTRODUCTION

Noise removal and image smoothing are important to many image processing applications. For example, Gaussian and median filtering are often used as preprocessing steps in color image quantization, motion estimation, and image segmentation.

For color images, a common approach to remove impulse noise is by vector median filtering (VMF) [1]. Other approaches include vector directional filtering (VDF) [14] and directional-distance filtering [9]. The latter is the combination of the VMF and VDF methods. One of the drawbacks of these methods is that they are typically implemented uniformly across the image and tend to modify pixels that are not corrupted by noise. In [3], a Teager-like operator is used to first detect the outliers so that only the noisy pixels are replaced. But the detection process is performed on each individual color component, which may cause errors in the final results.

For the case of mixed Gaussian and impulse noise, an adaptive nonlinear multivariate filtering method is proposed in [13]. However, because the mean of the entire local window is used to estimate the original pixel value, it may blur the edges and the details.

To address these drawbacks, a nonlinear algorithm called peer group filtering (PGF) is proposed for noise removal in color images. Let $x_0(n)$ denote an image pixel vector, characterizing the color information at position n centered in a $w \times w$ window. Sort all the pixels in the window according to their distances to $x_0(n)$ in ascending order and denote them as $x_i(n)$, $i = 0, \ldots, k = w^2 - 1$. The Euclidean distance measure is used here, i.e.,

$$d_i(n) = \|x_0(n) - x_i(n)\|, \quad i = 0, \ldots, k \tag{1}$$

$$d_0(n) \le d_1(n) \le \ldots \le d_k(n) \tag{2}$$

The peer group $P(n)$ of size $m(n)$ for $x_0(n)$ is defined as

$$P(n) = \{x_i(n), i = 0, \ldots, m(n) - 1\} \tag{3}$$

It consists of $x_0(n)$ itself and its neighboring points of similar colors. The concept of peer group is introduced in [8] for gray-scale image enhancing and noise removal. Here it is extended to color images and an automatic scheme is proposed to select the peer group size $m(n)$ for each pixel. The basic idea of PGF can be summarized in two steps:

1. **Classification:** classifying the peer group of each pixel $x_0(n)$. If it is decided that $x_0(n)$ belongs to impulse noise and does not have a peer group, the true peer group at that location is estimated by the rest of the pixels in the window.
2. **Replacement**: replacing $x_0(n)$ with the weighted average of its peer group members. This can be seen as Gaussian filtering with a binary mask where 1 indicates that the pixel is a peer group member.

The next section explains the PGF method in detail.

2. PEER GROUP FILTERING

The purpose of averaging over the peer group members instead of the entire local window is to avoid edge blurring. How to choose an appropriate size $m(n)$ for each peer group based on the local statistics is important to the success of the PGF algorithm. One approach could be setting a threshold $T(n)$, such that $m(n)$ satisfies

$$d_{m(n)-1}(n) \le T(n) \text{ and } d_{m(n)}(n) > T(n) \tag{4}$$

However, since the signal and noise statistics can change for different images or even within the same image, it is difficult to find a fixed value of $T(n)$ that is optimal.

If there are two clusters of colors in the window, the Fisher's linear discriminant [7] that maximizes the ratio of the inter-class scatter to the intra-class scatter can be used to separate the two clusters. However, for more than two classes, the approach will not be able to separate the cluster that contains the center pixel $x_0(n)$. Also, the computational complexity is high in 3-D space.

There is a simple way to circumvent these problems by using

This work was supported in part by a grant from Samsung Electronics and by ONR award #N00014-98-1-0515.

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only the $1D$ distances $d_i(n)$ for Fisher's discriminant estimation. The criterion to be maximized is

$$J(i) = \frac{|a_1(i) - a_2(i)|^2}{s_1^2(i) + s_2^2(i)}, \quad i = 1, \ldots, k \tag{5}$$

where

$$a_1(i) = \frac{1}{i}\sum_{j=0}^{i-1} d_j(n) \text{ and } a_2(i) = \frac{1}{k+1-i}\sum_{j=i}^{k} d_j(n) \tag{6}$$

$$s_1^2(i) = \sum_{j=0}^{i-1} |d_j(n) - a_1(i)|^2 \text{ and } s_2^2(i) = \sum_{j=i}^{k} |d_j(n) - a_2(i)|^2 \tag{7}$$

The algorithm computes $J(i)$ for each i and finds the cut-off position where $J(i)$ is the maximum, i.e.,

$$m(n) = \arg\max_i J(i) \tag{8}$$

Maximizing the criterion $J(i)$ can successfully separate two clusters of colors in the window. If there are more than two clusters, the one containing $x_0(n)$ can still be separated from the rest of the colors. If there is only one cluster of colors, the peer group will not contain all the points in the window. However, $x_0(n)$ will still be smoothed by its peer group members.

In order to remove the effect of impulse noise, the first order differences of the distances $d_i(n)$, $f_i(n)$, are calculated before the peer group classification:

$$f_i(n) = d_{i+1}(n) - d_i(n) \tag{9}$$

The following test is performed on the first and the last M points of $x_i(n)$ to check if they belong to impulse noise:

$$f_i(n) \le \alpha \tag{10}$$

where $M = w/2$, half of the window size, and α is set large for highly corrupted images and small for slightly corrupted ones. If $f_i(n)$ does not satisfy the condition, the end points $x_j(n)$ for $j \le i$ or $j > i$ are considered as impulse noise and removed. The remaining $d_j(n)$ are used to estimate the true peer group.

The underlying assumption used in the above approach is that if $x_0(n)$ belongs to impulse noise, it tends to be far away from other points in the window. This can be detected by the values of $f_i(n)$. To eliminate other possible noise in the window that can affect the results of peer group classification, the first and the last M points are also tested.

After the impulse noise removal and the peer group classification, the pixel $x_0(n)$ is replaced by the weighted average of its peer group members

$$x_{new}(n) = \frac{\sum_{i=0}^{m(n)-1} w_i p_i(n)}{\sum_{i=0}^{m(n)-1} w_i}, \quad p_i(n) \in P(n) \tag{11}$$

where w_i are the standard Gaussian weights depending on the relative positions of $p_i(n)$ with respect to $x_0(n)$.

If the purpose is to remove impulse noise and not to smooth the image, the first M points are tested by Eqn. (10). If any one point fails the test, $x_0(n)$ is considered as noise. The peer group in this special case has only one member which is the vector median [1] of the local window. The difference between vector median filtering and PGF is that PGF determines whether a pixel is corrupted before replacing it, while VMF replaces all the pixels regardless whether they are noise or not.

3. COLOR IMAGE QUANTIZATION

We now apply peer group filtering to the color quantization application. Color quantization techniques have been studied for many years. Some of the recent work includes a mean shift algorithm for clustering [4], a genetic algorithm for the initialization of the C-means algorithm [12], and a quantization scheme in the HSI color space [11]. However, these methods restrict the analysis to the color space only and do not take into account the spatial distribution of the colors, which affects the quantization results.

It is observed that human vision perception is more sensitive to the changes in smooth regions than in detailed regions. Accordingly, colors can be more coarsely quantized in the detailed regions without affecting the perceptual quality significantly. To exploit this fact, a weight is assigned to each pixel based on the variance in the local window such that pixels in the smooth regions have more importance than pixels in the detailed regions [2], [10].

The approach in this work uses local statistics obtained after peer group filtering as the weights in the vector quantization (VQ) process. The complete color quantization procedure is as follows:

1. First, peer group filtering is applied to the image for smoothing and noise removal.
2. As a result, the maximum distance of each peer group $T(n)$, $T(n) = d_{m(n)-1}(n)$ is obtained. The value of $T(n)$ indicates the smoothness of the local region. The weight of each pixel $v(n)$ is calculated by
$$v(n) = \exp(-T(n)) \tag{12}$$
Pixels in the noisy regions are weighted less than pixels in the smooth regions.
3. The average of $T(n)$, T_{avg} indicates the smoothness of the entire image. In general, the higher the T_{avg}, the less smooth the image is and more clusters are needed to quantize the colors in the image. The initial number of clusters N in VQ is estimated by
$$N = \beta T_{avg} \tag{13}$$
where β is set to 2 in the experiments.
4. The generalized Lloyd algorithm (GLA) is used in VQ. The update rule is modified to incorporate the pixel weights. For a color cluster C_i, its centroid c_i is calculated by
$$c_i = \frac{\sum v(n)x(n)}{\sum v(n)}, \quad x(n) \in C_i \tag{14}$$
The centroids are shifted towards points with higher weights.
5. The initial clusters for GLA is determined by the popular splitting initialization algorithm. The weighted distortion measure, defined as
$$D_i = \sum v(n)\|x(n) - c_i\|^2, \quad x(n) \in C_i \tag{15}$$
is used to determine which clusters to split until the initial number of clusters N is reached. Thus, points with smaller weights will be assigned fewer clusters. so that number of color clusters in the detailed regions are suppressed.
6. In the final step of VQ, the cluster centroids are calculated without pixel weights to obtain the true cluster centers. Sometimes, a large numbers of pixels having the same color will have more than one cluster because GLA is aimed to minimize the global distortion. Therefore, an agglomerative clus-

tering algorithm [7] is performed on the cluster centroids to further merge close clusters such that the minimum distance between two centroids satisfies a preset threshold. The final quantized image is obtained by assigning each pixel with its closest cluster centroid.

4. EXPERIMENTAL RESULTS

To test the effectiveness of peer group filtering for impulse noise removal (no smoothing), the pixels of "baboon" and "pepper" images are corrupted by randomly generated impulse noise. Different percentages of the total pixels are corrupted. The PGF method is compared to VMF [1] and the Teager-operator method (TEA) [3]. Window size w is 3×3 and color space is RGB for all the methods. The α parameter in both PGF and TEA is tuned to obtain best results for each case. The results are tabulated in Table 1 and Table 2. The "None" columns indicate SNR without any noise removal. It can be seen from the tables that PGF gives the best results for all the cases. Fig. 1 shows the actual results on a small area in the "baboon" image, where the center pixel is corrupted. VMF removes the noise but also changes the color of other pixels while TEA fails to replace the noise with a similar color to the original one. As can be seen from Fig. 1(e), PGF results best approximation to the original image.

Fig. 2 illustrates the use of PGF for color image smoothing. A part of the "baboon" image is shown enlarged for a clearer view. The result of Gaussian filtering is also shown for comparison. Window size w is 5×5 and color space is RGB for both PGF and Gaussian filtering. $\sigma^2 = 1.0$ for the Gaussian weights. It can be seen from the figure that PGF smooths the image without blurring the details compared to Gaussian filtering.

Fig. 3 and Fig. 4 show the results of PGF and very coarse color quantization for "baboon" image and an image from the "flower garden" video sequence. To preserve the color quality, all the processing is done in the perceptual uniform CIE LUV color space. In both cases, $w = 5$, $\sigma^2 = 1.0$, $\alpha = 12$. The "baboon" image is quantized to only 18 colors and the "flower garden" image is quantized to only 13 colors. Both quantized images still preserve the majority of the color information in the original images and maintain a certain image quality.

The original color images used in the experiments can be obtained from http://vivaldi.ece.ucsb.edu/users/deng/PGF.

After the quantization, the color information in each image can be represented by a very few number of colors. This is useful in our new color image segmentation algorithm [6]. The color quantization is also used to create an efficient color feature representation for image search and retrieval [5].

5. CONCLUSIONS

In this work, peer group filtering, a nonlinear algorithm for image smoothing and impulse noise removal in color images is presented. The algorithm effectively removes the noise and smooths the color images without blurring the edges and the details. Local statistics obtained after PGF are used in the color quantization to achieve perceptual color quantization. Results show that very coarse quantization can be obtained while preserving the color information in the original images. The results of color quantization can be used in the color image segmentation and color image retrieval applications.

6. REFERENCES

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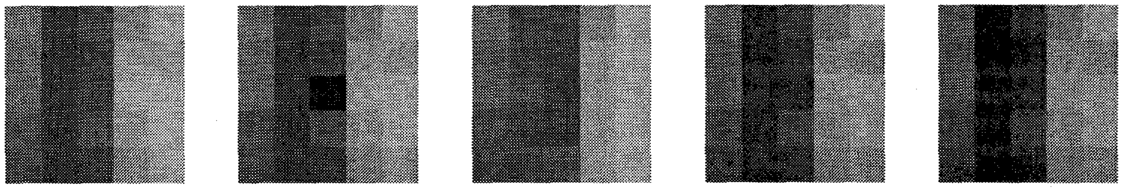
Table 1: SNR for "baboon" image (dB)

noise %	None	VMF	TEA	PGF
1%	24.05	18.06	30.19	32.46
5%	17.03	17.88	24.42	26.41
10%	14.02	17.61	21.79	23.60
20%	10.97	17.07	18.67	20.56

Table 2: SNR for "pepper" image (dB)

noise %	None	VMF	TEA	PGF
1%	23.35	30.90	38.92	41.17
5%	16.34	28.80	31.77	34.64
10%	13.33	26.99	28.04	31.15
20%	10.30	24.72	24.22	27.35

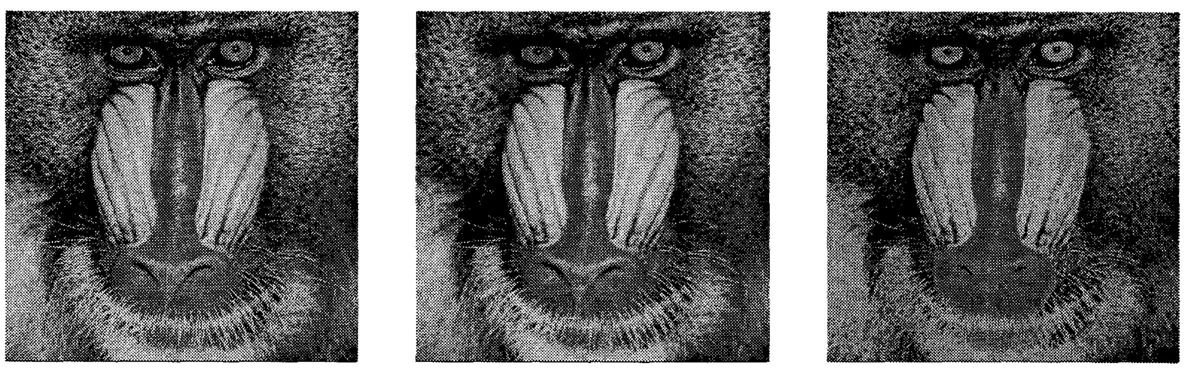


(a) (b) (c) (d) (e)

Fig 1. (a) a small area of the original "baboon" image, (b) same area of the 5% corrupted image, (c) results of VMF, (d) results of TEA, (e) results of PGF.

(a) (b) (c)

Fig 2. (a) part of the original "baboon" image, (b) results of PGF, (c) results of Gaussian filtering.



(a) (b) (c)

Fig 3. (a) original "baboon" image (512x512), (b) results of PGF, (c) results of quantization with 18 colors.

(a) (b) (c)

Fig 4. (a) original image from the "flower garden" video (352x240), (b) results of PGF, (c) results of quantization with 13 colors.