ABSTRACT

Color quantization is to design a color palette having almost no noticeably perceived difference between original and quantized images. In this paper, to design such a palette, the color quantization algorithm is considered in two parts: the selection of a proper distortion measure and the design of an optimal palette. The proper selection of distortion measure in the quantization is important to image quality. Since the human eye is the final judge of image quality, it is desirable to use a perception-based distortion measure. Thus we developed an activity-weighted distortion measure considering color visual sensitivity and absorbtance of human visual system(HVS) depending on each color component in the local region of image. Then using the distortion measure, a hierarchical quantization algorithm is proposed. The algorithm consists of initial and subdivision steps both to reduce computation time and to minimize the distortion based on spatial masking effect of HVS. The experimental results show that the proposed algorithm shows better visual quality and less computation time comparing to the conventional algorithms.

1. INTRODUCTION

Video monitor displays color image by modulating the intensity of three primary colors(red, green, and blue) at each pixel of the color image. In a digitized image, each primary color is usually quantized with 8 bits of resolution in order to eliminate distinguishable quantization steps in tri-chromatic specification (luminance, hue, and saturation). Thus, full-color digital display systems use 24 bits to specify the color of each pixel on the screen. However, the cost of high-speed memory needed to support such display on the high-resolution monitor makes many applications impractical. An alternative approach in many currently available displays is to provide a limited number of bit, such as 8 bits, for specifying the color at each pixel. Each of these $2^8$ values is then used as an index into user-defined table of color, i.e., color palette. Each entry in the table contains a 24-bit value that specifies each primary component of the color image. In this way, the user is allowed to select a small subset of color palette from the full range of $2^{24}$ colors. The drawback of this scheme is that it restricts the number of colors that may be simultaneously displayed\[1-7\].

Since natural images typically contain a large number of distinguishable colors, displaying such images with a limited palette is difficult. Several techniques exist for color quantization, some of which are based on a more general class of vector quantization(VQ) techniques. One approach involves the iterative refinement of an initially selected palette. Variations on this idea include the manner in which the initial palette is chosen and the color space in which the quantization is performed. The refinement algorithm, commonly known as the K-means or Linde-Buzo-Gray(LBG) algorithm\[1\], is a vector extension of the Lloyd quantizer for scalars. It seeks to reduce the total squared error(TSE) between the original and the quantized image at each iteration until a (local) minimum is found. This method yields high-quality images and, with a properly chosen initial palette, will result in the lowest TSE for a given palette size. It is, however, computationally intensive and its performance is sensitive to the choice of the initial palette. Also there is a class of splitting algorithms\[2,3,6\] that divide the color space into disjoint regions and pick a representative color from each region as a palette color. The algorithms vary according to the methods used to split the color space. As an example of such algorithm, the median-cut algorithm\[2\] invented by Heckbert was undertaken as an alternative to the popularity algorithm. The median-cut algorithm repeatedly subdivides the color space into smaller rectangular boxes until the desired number of boxes is generated. The split point is the median point - the plane which divides the box into two halves so that equal numbers of colors are on each
side. The main advantage of the split algorithm is that it has a lower computational time cost and space for the spatial storage scheme-mostly because it is simple to compute the split point. There remain, however, a number of problems associated with this method. One of those is that partitioning a box by a plane passing through the median point does not necessarily lead to a lower quantization error.

As explained above, the conventional color quantization algorithms usually use the TSE as the distortion measure[9,13]. This measure is, however, perceptually insufficient when accurately estimating the perceptual difference between an original image and its quantized representation. It does not take into account the spatial correlations that linked perceptually adjacent pixels. With such a measure we have no means to know whether the observed degradations are the result of several particularly noticeable degradations. The measure must be reconsidered, this time, by duly integrating the notion of locally observable errors. Thus, we propose to use a new distortion measure that takes into account the spatial activity in local region of input image. The activity is computed as mean of coefficient-weighted difference between input color and local mean color in 4 local region of the image, as given below.

\[ A(c_{i1:16}) = \sqrt[16]{\sum_{i=1}^{16} \Delta(c_{i1}, c_{im})} \]

where \( \Delta(c_{i1}, c_{im}) = \sum_{j} \{ \alpha(a_{ij} - c_{im})^2 + \beta(b_{ij} - c_{im})^2 + \gamma(g_{ij} - c_{im})^2 \}^{1/2} \)

2. THE PROPOSED DISTORTION MEASURE AND QUANTIZATION ALGORITHM

The color quantization is usually done by treating three color components (red, green, and blue) independently in RGB color space. Although three color components can be decorrelated by transforming the color space to YIQ, Lab or other uniform color spaces, independent quantization in these spaces is inefficient because certain portion of these spaces lies outside the RGB color space. In any event, color transformations are of little use in quantization for display; their proper place is in image compression systems. Thus, we adopted to quantize the colors of original image into \( K \) (usually \( K=256 \) or less) colors, called color palette, in the RGB color space.

The color image is assumed to be on a rectangular grid of \( N (= M \times M, M: \text{image size}) \) pixels. The set of all grid points is denoted by \( S \) and its members \( s \in S \) may be explicitly written as \( s=(i,j) \), where \( i \) and \( j \) are the row and column indices, respectively \((0 \leq i,j < M - 1)\). The color value of the pixel at grid point \( s \) is denoted \( c_{is} = [r_{is}, b_{is}, g_{is}]^T \) where the components are the red, green, and blue tristimulus values for the pixel in the RGB color space and superscript \( T \) means transpose. And in designing the color palette, the \( k \)-th cluster of colors is denoted by \( Q_k \) \((1 \leq k \leq K)\) and the centroid of the cluster is denoted by \( c_k = [r_{ik}, b_{ik}, g_{ik}]^T \) which composes the color palette. The input image colors are mapped to the centroid colors after the quantization and the mapped colors are displayed on the monitor simultaneously.

2.1 ACTIVITY-WEIGHTED DISTORTION MEASURE

In this paper, to design the color palette having almost no noticeably perceived difference between the input image and the reconstructed image, the color quantization problem is considered in two parts: the selection of a proper distortion measure and the design of an optimal color palette using the distortion measure. A basic and important concept in the color quantization is the distortion measure used to measure the quantization errors between input colors and palette colors. Since the human eye is the final judge of quantized image quality, it is desirable to use a perception-based distortion measure. Thus, we develop an activity-weighted distortion measure based on the color change stimuli of the HVS according to each color component in the local region of color image. In order to measure the perception-based distortion, first, the color activity is computed as mean of coefficient-weighted difference between input color and local mean color \( c_{lm} = [r_{lm}, b_{lm}, g_{lm}]^T \) in 4x4 local region of the image, as given below.

\[ A(c_{i1:16}) = \sqrt[16]{\sum_{i=1}^{16} \Delta(c_{i1}, c_{im})} \]

where \( \Delta(c_{i1}, c_{im}) = \sum_{j} \{ \alpha(a_{ij} - c_{im})^2 + \beta(b_{ij} - c_{im})^2 + \gamma(g_{ij} - c_{im})^2 \}^{1/2} \)

and

\[ \alpha = S_{a} / (S_{a} + S_{b} + S_{r}) \]

\[ \beta = S_{b} / (S_{a} + S_{b} + S_{r}) \]

\[ \gamma = S_{r} / (S_{a} + S_{b} + S_{r}) \]
where the $R_s$, $G_b$, and $B_s$ are the visual sensitivity, and the $R_4$, $G_b$, $B_s$ each color component at wavelength $\lambda$
coefficients show the response rate of human eye(cone) to each
color component. Then the computed activity shows the degree
thus, makes the proposed measure the perception-based
distortion measure. The activity value is samely assigned to all
quantization error of color. The higher activity means that the
color is less sensitive to human vision whereas the lower activity
effect, a characteristic of HVS which means that human vision is
the edge region.
And then, using the computed activity, the proposed distortion
\[
D_k = \sum_{l=1}^{K} D_{lk} = \sum_{l=1}^{K} \frac{1}{A(l_{sT})^2} \left\| P_x - \mu_k \right\|^2
\]
where $D_k$ is the distortion of $k$-th color cluster, $E_q$ is the
quantization error. As the input color is included in the $k$-th
cluster, the quantization error is divided by the activity value of
the input color. If so, the distortion error is decreased by the
activity. Therefore, if the input color is less sensitive color, the
activity is much higher and the distortion error is relatively much
decreased. And if the input color is more sensitive color, the
activity is much lower and the distortion error is relatively less
decreased. This characteristic shows the masking effect. Thus,
using the distortion measure, the less sensitive color can be less
quantized, whereas the more sensitive color can be more finely
quantized.

2.2 HIERARCHICAL QUANTIZATION ALGORITHM

Using the distortion measure, a hierarchical color quantization
algorithm is proposed by considering the masking effect. The
algorithm consists of initial and subdivision steps both to reduce
the computational time and to minimize the quantization errors.
In the initial step, the input colors are divided into 8 initial color
clusters, and then in the subdivision step, the initial color
clusters are recursively divided into $K$(256 or less) color clusters
using the proposed distortion measure. In both steps, inter-
cluster variance maximization method is used to determine the
quantization threshold level, which is fast and efficient in
thresholds calculation. The proposed algorithm is shown in Fig.
3.

Then, the input colors are mapped to the centroids of the color
clusters using the pairwise-nearest neighbor method. The mapped
colors compose the color palette and are reconstructed on
the video monitor simultaneously.

3. EXPERIMENT AND RESULTS

To simulate the proposed quantization algorithm, 256×256 Girl,
Lena, Pepper and Zelda images are used. These images contain
both smooth and edge regions and we can see the effect of the
activity. For the original image, the activity in each 4×4 local
region is computed and the values are samely assigned to all the
pixels in the region. Then we start the hierarchical quantization
algorithm. In the initial quantization step, three thresholds are
calculated using the inter-cluster variance maximization method.
The three acquired thresholds for Girl image are shown in Fig. 4.
Depending on the thresholds, 8 initial clusters are decided using
the following equation.

\[
\begin{align*}
\text{cluster 1 :} & \quad r, < R_1, \quad g, < G_1, \quad \text{and} \quad b, < B_1 \\
\text{cluster 2 :} & \quad r, < R_1, \quad g, < G_1, \quad \text{and} \quad b, \geq B_1 \\
\text{cluster 3 :} & \quad r, < R_1, \quad g, \geq G_1, \quad \text{and} \quad b, < B_1 \\
\text{cluster 4 :} & \quad r, < R_1, \quad g, \geq G_1, \quad \text{and} \quad b, \geq B_1 \\
\text{cluster 5 :} & \quad r, \geq R_1, \quad g, < G_1, \quad \text{and} \quad b, < B_1 \\
\text{cluster 6 :} & \quad r, \geq R_1, \quad g, < G_1, \quad \text{and} \quad b, \geq B_1 \\
\text{cluster 7 :} & \quad r, \geq R_1, \quad g, \geq G_1, \quad \text{and} \quad b, < B_1 \\
\text{cluster 8 :} & \quad r, \geq R_1, \quad g, \geq G_1, \quad \text{and} \quad b, \geq B_1
\end{align*}
\]

where $r_s$, $g_s$, and $b_s$ are input color components of the pixel at
grid point $s$, and $R_1$, $G_1$, and $B_1$ are the calculated thresholds. In
the subdivision step, the cluster distortions($D_k$) are computed
using Eq. (2). Then, a maximal distortion cluster is selected and
subdivided into 8 clusters using the above method. This process
is repeated until $K$ color clusters are acquired, as shown in Fig. 3.

Fig. 5 shows the comparison of displayed image on the
monitor using the conventional quantization algorithms and the
proposed algorithm. The proposed algorithm shows better visual
quality. And Table 1 has the comparison of the PSNR,
quantization errors in uniform color coordinate system space,
and computation time using Sun Sparc Workstation in each
algorithm. In the table, the proposed algorithm takes a little
longer computation time than the Heckbert’s algorithm but it
takes much shorter computation time than LBG.

4. CONCLUSIONS

We have proposed an efficient color quantization algorithm for
designing a color palette which has almost no noticeably
perceived error and achieves high visual quality. Since the
human eye is the final judge of quantized image quality, the
weighted distortion measure based on HVS color activity was considered. With this measure, we could estimate the perceptual difference between input image and quantized representation as a degree of color change stimuli on the human vision in the local region of an image. And the proposed hierarchical quantization algorithm could produce an improved color palette by recursively subdividing a color cluster having maximal quantization error computed by the proposed measure.

The performance of our quantization algorithm is comparable to that of the optimal LBG algorithm under PSNR and RMSE of quantization error in the CIE uniform color space, but it has much shorter computation time. Another advantage of the proposed algorithm is that it shows better image quality without any post-processing such as ordered dithering, error diffusion, or erosion methods commonly used in other algorithms.

REFERENCES

Fig. 4. Activity distribution in the intensity level of each color component and three thresholds ($R_t$, $G_t$, and $B_t$) acquired in the initial step of the proposed algorithm using Girl image.

Table 1. The comparison of PSNR, quantization errors ($Q_e$) in CIE($L^*u^*v^*$), and computation time using Sun Sparc Workstation in each algorithm

<table>
<thead>
<tr>
<th>Image</th>
<th>Algorithm</th>
<th>PSNR [dB]</th>
<th>$Q_e$ in $L^*u^<em>v^</em>$</th>
<th>Time [sec]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Girl</td>
<td>LBG</td>
<td>30.6</td>
<td>15.13</td>
<td>4150</td>
</tr>
<tr>
<td></td>
<td>Heckbert</td>
<td>28.86</td>
<td>22.86</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>The proposed</td>
<td>30.87</td>
<td>11.37</td>
<td>24</td>
</tr>
<tr>
<td>Lena</td>
<td>LBG</td>
<td>30.15</td>
<td>5.37</td>
<td>2307</td>
</tr>
<tr>
<td></td>
<td>Heckbert</td>
<td>29.80</td>
<td>6.20</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>The proposed</td>
<td>31.83</td>
<td>4.56</td>
<td>24</td>
</tr>
<tr>
<td>Pepper</td>
<td>LBG</td>
<td>28.92</td>
<td>8.72</td>
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</tr>
<tr>
<td></td>
<td>Heckbert</td>
<td>25.88</td>
<td>19.57</td>
<td>11</td>
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<tr>
<td></td>
<td>The proposed</td>
<td>29.28</td>
<td>8.42</td>
<td>24</td>
</tr>
<tr>
<td>Zelda</td>
<td>LBG</td>
<td>31.71</td>
<td>4.08</td>
<td>1828</td>
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<tr>
<td></td>
<td>Heckbert</td>
<td>29.66</td>
<td>5.29</td>
<td>11</td>
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<tr>
<td></td>
<td>The proposed</td>
<td>34.80</td>
<td>3.35</td>
<td>24</td>
</tr>
</tbody>
</table>

Fig. 5. The experimental results using Girl image.