Image Analysis Applications and Computer Graphics, Proc.ICSC-95 p.389-396, Dec 1995

Time-Space Weighting for Image Sequence Quantization

Hagit Zabrodsky Hel-Or

Dept. of Psychology, Stanford University, Stanford, CA. 94305
e-mail: gigi@white.stanford.edu

Abstract. This paper introduces a method for quantization of image-sequences which takes into account the human sensitivities in both space and time. A weighted clustering approach is used for quantization which allows flexibility in the choice of weights. Assigning weights proportional to the space gradients and the time gradients is shown to produce better quantization of color image sequences.

1 Introduction

As memory costs decrease, most computers are capable of displaying images and image sequences. However, many of the color display devices are still restricted in video-memory, allowing only a limited number of colors to be displayed simultaneously. The most common color display has 8-bit video memory allowing only $2^8 = 256$ simultaneous colors. Most images, and certainly image sequences, contain more than the limited number of colors allowed on the display, therefore a scheme for representing these images with a lower color count than the original, must be used.

Color *quantization* is the process of selecting a maximally allowed set of colors (denoted the color palette or color map) and reproducing the original image with this color set. The quantization process aims at producing a quantized image which is as similar as possible to the original. The quantized image is usually represented by a color map and an assignment mapping the pixels of the original image to the entries in the color map. When dealing with color image sequences the problem of quantization is two-fold: not only is a color map to be produced for each frame, the color continuity between frames must also be maintained. Thus, the quantization process for image sequences must aim at reproducing the original as accurately as possible while reducing the flicker and unwanted color changes between frames. In this paper a method for quantization of image-sequences is introduced which takes into account the human sensitivities in both space and time. This will increase color reproduction while reducing color flicker and color inconsistencies between frames.

2 Image Quantization

Color quantization has been widely discussed in the context of still images. A variety of approaches have been suggested. The quantization schemes can be divided into two main schemes: image independent and image dependent.

Image independent schemes assume a color map independent of image content. These color maps are usually chosen to include colors equally spaced and covering the full gamut of possible colors. Each pixel color in the the original image is mapped into its closest quantized value in the color map. The image independent schemes are usually time-efficient but produce a poor color reproduction of the original image.

Image dependent schemes are the more widely discussed methods. They produce better color reproductions though at the expense of greater computation time and larger memory requirements. Under the image dependent category, several directions have been suggested:

- Iterative or error minimization approaches, define an error measure that evaluates the visual error between a given quantized image and the original. The quantization process proceeds by iteratively refining a given color map so that the error measure is minimized. Examples of this approach can be found in [5, 15, 9, 19, 24].
- Bottom-up approaches to quantization, perform clustering on the colors of the original image. The clustering in these methods is initialized with many clusters (in most cases every color in the original image is considered an individual cluster). The quantization method continuously merges the two nearest clusters, until the number of clusters equals the number of entries allowed in the color map. Examples of this approach are [6, 20, 7, 3].
- Top-down approaches to quantization, also perform clustering on the colors of the original image. However in these methods the clustering is initialized with a single cluster (which contains all the colors of the original image). The quantization method continuously splits the most appropriate cluster into two clusters. The process terminates when the number of clusters equals the number of entries allowed in the color map. [11, 22, 21, 23, 17, 4]. Top-down approaches vary in their criteria for choosing the cluster to be split and in the method of splitting the cluster. In [11] the cluster to be split is chosen as the most elongated cluster and the split is performed by dividing the colors of the cluster at the median along the longest axis of distribution spread. The clusters in this method are always split parallel to the color space axes (RGB), thus the final clusters obtained are always rectangular. Later approaches [22, 21, 23] choose the cluster to be split as that having the greatest variance (not necessarily parallel to the color space dimensions), thus the final clusters obtained are general polytopes.

The methods mentioned above, though image dependent, generally do not explicitly take into consideration the human observer. Image quantization can be improved by incorporating human sensitivity considerations. This has been shown to be successful in quantization and dithering of still images [17, 4, 16, 1]. Experimental studies have shown that human sensitivity to quantization errors increases as the spatial gradient of the image decreases. Thus two pixels in an image having the same color should influence the quantization process differently depending on the spatial gradients of the image at these pixel locations. In [17, 4], human sensitivity dependent on spatial frequency was incorporated into the quantization scheme by weighting the color of each pixel with a value inversely proportional to the intensity gradient at the pixel location. The weighted colors of the image are then clustered using a top-down quantization scheme which recursively divides the existing clusters until the required number of clusters is obtained.

3 Image Sequence Quantization

When quantizing image sequences, a color map is created for every frame in the sequence with the goal of reproducing the original sequence as accurately as possible. This goal demands obtaining:

1. good *color reproduction*, i.e colors in the quantized frame should be as similar as possible to the original.
2. good *color continuity*, i.e objects and regions appearing in contiguous frames, should be similar in color. This reduces flickering and unwanted color drifts between frames.

As a natural extension to quantization of still images, quantization of image-sequences is based on the methods mentioned in Section 2 for image quantization.

In this paper a method for image-sequence quantization is presented which incorporates human spatial and temporal sensitivities. The image quantization method on which the sequence quantization will be based, is that of Orchard and Bouman [17] described in Section 2. As mentioned, this method incorporates human spatial sensitivities using a weighting scheme. The method will be extended to incorporate human temporal sensitivities.

Adaptive quantization of image sequences has been previously presented [8, 18], however they do not take into consideration human sensitivities which is central to improving performance. Human models of temporal sensitivities have been incorporated in dithering and half-toning of image-sequences (see [2, 13, 12, 10]) but these schemes all assume a previously determined color map.

4 Improving Image Sequence Quantization

Throughout this paper, the quantization schemes are demonstrated on a synthesized test sequence (see Figure 3). The sequence chosen was artificially synthesized to include a large range of colors and to have constant regions and moving regions. The sequence depicts a series of color textures moving in the background with a single colored pattern serving as a stable foreground.

To emphasize the quantization affects, the test sequence is always quantized to produce a color map for each frame, having only 16 entries. However, even on color displays that can display 256 simultaneous colors, the quantization affects (poor color reproduction and poor color continuity) are significant.

In a systematic discussion of quantization of image-sequences two extreme approaches can be considered:

- Every frame of the sequence is quantized separately as a still image. Figure 4 shows a sequence quantized per frame using weighted clustering [17].
- All frames are quantized *in batch* as a single image (ie a concatenated image is produced from all frames). Figure 5 shows a sequence quantized in batch using weighted clustering. The same colormap is assigned to all frames.

As can be seen in Figure 4 and Figure 5, quantization of each frame separately produces a good reproduction of the original, however continuity of color is not maintained between frames (notice the color changes of the stable foreground patch). This loss of continuity will produce flickering and color instability when viewing these quantized frames as a time sequence. On the other hand, quantizing all frames in a single batch will produce color continuity (the foreground patch has constant color values throughout the sequence) however maintaining continuity is at the expense of reproduction quality: the quantized sequence is a poor reproduction of the original (notice the background in frame 2-3).

A natural hybrid approach to control the tradeoff of these two methods, is to create color maps by quantizing several but not all frames in batch. Thus a color map for frame i will be created by quantizing the concatenation of frames $i-m, \ldots, i, \ldots, i+m$. Figure 6 shows a sequence quantized by concatenating 3 frames in batch ($m = 1$). It can be seen that there is an improvement in color reproduction (compare with Figure 4) and in color continuity (compare with Figure 5). The tradeoff between color reproduction and color continuity is determined by the number of frames quantized per batch (the value of m). This is shown in Figure 1 where the error in color reproduction and in color continuity are presented as a function of the number of frames quantized per batch ($m * 2 + 1$). The error in color reproduction is given by a weighted root-mean-square measure (WRMS) taken over all pixels of the sequence. The error in color continuity is measured only over the pixels of the constant foreground patch. The error is given by the average of the WRMS errors measured between the contrast foreground patch of a given frame and that of the preceding frame. Note, we presume no perceptual comparison between the two error measures and present Figure 1 only to afford a qualitative evaluation of the tradeoff between color reproduction and color continuity.

5 Weighted Quantization

As mentioned in Section 1, improvement in quantization can be obtained by incorporating human sensitivity considerations. This has been shown to be successful in quantization of still images. In [17], human sensitivity dependent on spatial frequency was incorporated into the quantization scheme by weighting each pixel of the image to be quantized with a weight inversely proportional to the intensity gradient of the image at the pixel location. The weighted pixels

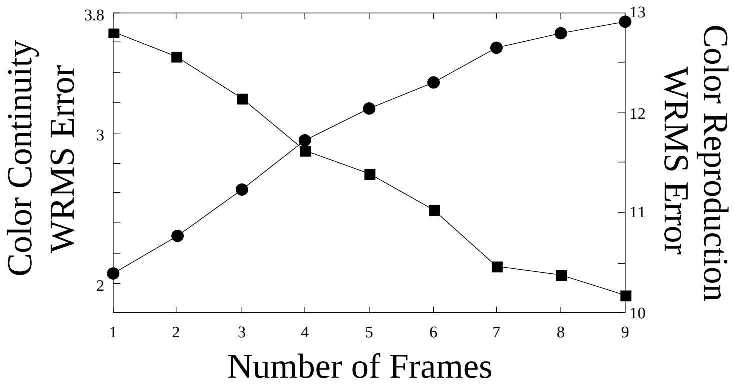

Fig. 1. Error as a function of number of frames quantized per batch. Evaluation of the color reproduction error (disks) and the color continuity error (squares).

of the image are then clustered using a weighted clustering scheme which recursively divides the existing clusters until the required number of clusters is obtained.

In this presentation, human sensitivity to temporal frequency is incorporated into the quantization scheme for image-sequences. Human sensitivity to contrast, chromaticity and color change is greatly reduced as temporal gradients increase [14]. In terms of quantization, objects or regions moving at high velocities should be assigned fewer resources in the quantization process. Accordingly, we assign a weight to every pixel in the image-sequence which is inversely proportional to the pixel velocities.

In the scheme presented here, the combination of the spatial-weights and the temporal-weights is multiplicative.

5.1 Time Dependent Weighting

Two time dependent weightings should be considered when quantizing image-sequences:

- *Time-Frame* weighting - When quantizing frames $i-m, \ldots, i, \ldots, i+m$ the pixels of the current frame (i) should be weighted more than pixels of previous and later frames. This weighting should be applied since the pixels of the current frame will be displayed using the color map obtained from the quantization process, whereas the pixels of the previous and later frames are considered only for color continuity. Increasingly smaller weight can be used for distal frames. Figure 7 shows the quantization of a sequence when three frames are quantized per batch ($m=1$) and both spatial weighting and time frame weighting are used. The time-frame weighting are 1:2:1 for the pixels of frame $i-1, i$ and $i+1$, respectively (thus the weights determined from the spatial gradients are doubled for the pixels of frame i).

- *Temporal Frequency* weighting- As mentioned above, at high temporal gradients (when objects or regions are moving at high velocity in the image sequence), sensitivity to color accuracy and to color changes decreases. At low temporal gradients (specifically when regions in the image remain constant over several frames) sensitivity is maximal. Thus appropriate temporal frequency weighting is inversely proportional to the temporal gradients of the sequence. The temporal frequency weights can be evaluated by finding the velocity (or temporal gradient) at each pixel location for each frame of the image sequence. Given that the image sequence is discrete in space and time, we can evaluate velocities by obtaining estimations of the optical flow at each pixel location. This is done using correlation based techniques. In the synthesized sequence used in the examples, the optical flow is zero over the pixel of the foreground patch and is a constant vector over the background textures. Figure 8 shows the quantization of a sequence when three frames are quantized per batch ($m = 1$) and the weighting combines spatial weighting, time-frame weighting and temporal frequency weighting. The time-frame weighting are 1:2:1 for the pixels of frame $i-1, i$ and $i+1$, respectively and the temporal frequency weights are 20 for the foreground patch pixels and 2 for the background pixels. The final weight for each pixels is given by the multiplication of the three assigned weightings.

Qualitative evaluation of the space-time weighting scheme for quantization of image sequences is given in the graph of Figure 2. The error measures previously described for color reproduction and color continuity (Section 1) were applied to the results of quantization of the test sequence using different quantization approaches:

- Quantization of each frame separately.
- Quantization of all frames in a single batch.
- Every three frames are quantized per batch (variable m described in Section 1 is equal to one). In this scheme only spatial weights are used.
- Every three frames are quantized per batch, both spatial weights and time-frame weights are used.
- Every three frames are quantized per batch, spatial weights, time-frame weights and temporal frequency weights are used.

6 Conclusion

In this paper, quantization of image sequences was discussed. A new approach was presented where human sensitivity in both spatial and temporal dimensions is considered in the quantization process.

The human sensitivity is incorporated into the quantization process by assigning weights to the pixels of the sequence which are then clustered using a weighted clustering scheme. The weights determine the proportion of resources

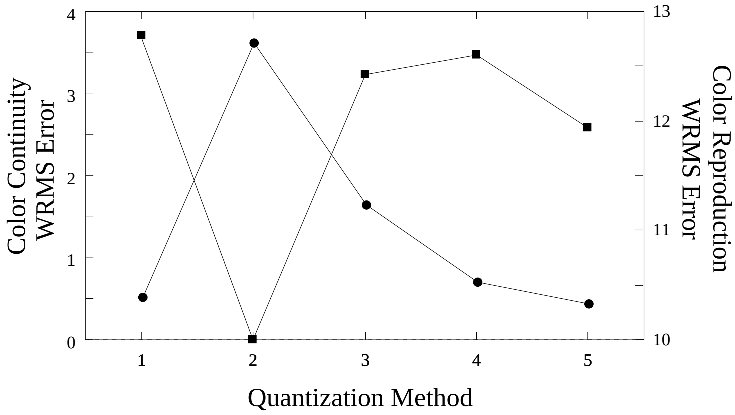

Fig. 2. Evaluation of the color reproduction error (disks) and the color continuity error (squares) for different quantization methods:

1. Quantizing each frame separately.
2. Quantizing all frames in a single batch.
3. Quantizing 3 frames in every batch.
4. Quantizing 3 frames in every batch and including both spatial weighting and time-frame weighting.
5. Quantizing 3 frames in every batch and including spatial weighting, time-frame weighting and time-frequency weighting.

allocated to each pixel in the aim of allocating fewer resources to those pixels of low human sensitivity.

The weighting scheme used for quantization can be extended to interest and target driven weighting: weights can be assigned to pixels according to the 'importance' or 'interest' of those pixels irrelevant of their spatial and temporal gradients. Some applications may prefer larger weights (and better color reproduction and continuity) to be assigned to specific objects or specific regions of space and time in the image sequence. For example, in image reproduction it is important to create a good reproduction of skin tones. Thus the weighting scheme for quantization can be used by assigning larger weights to pixels of faces.

Finally, instead of considering the weight assigned to each pixel as a multiplication of distinct weights: spatial weights and temporal weights, one may approach the weight determination problem in space and time simultaneously by considering the space-time gradients of pixels in the 3D cube created by stacking the sequence frames.

[1] Color versions of Figures 3-8 can be obtained at ftp://white.stanford.edu/users/gigi

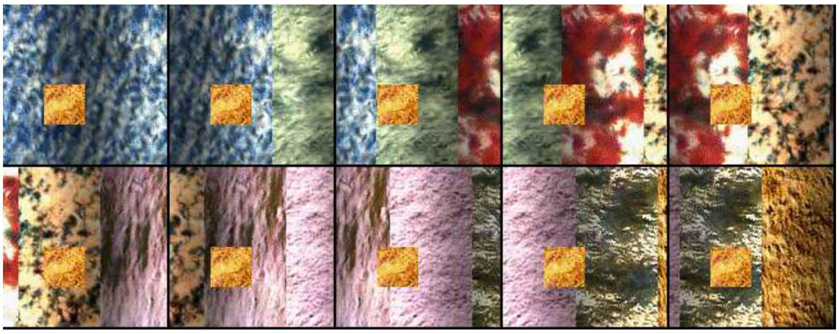

Fig. 3. A synthesized image sequence with 10 frames.

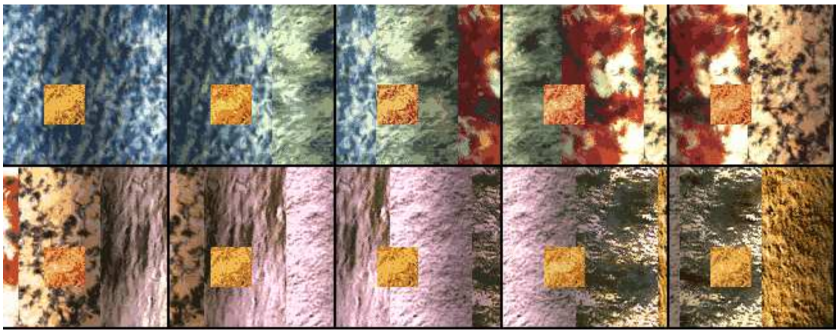

Fig. 4. Image sequence quantization by quantizing each frame separately.

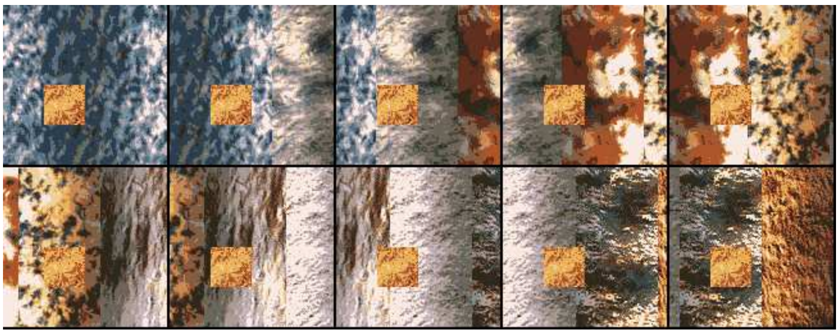

Fig. 5. Image sequence quantization by quantizing all frames in a single batch.

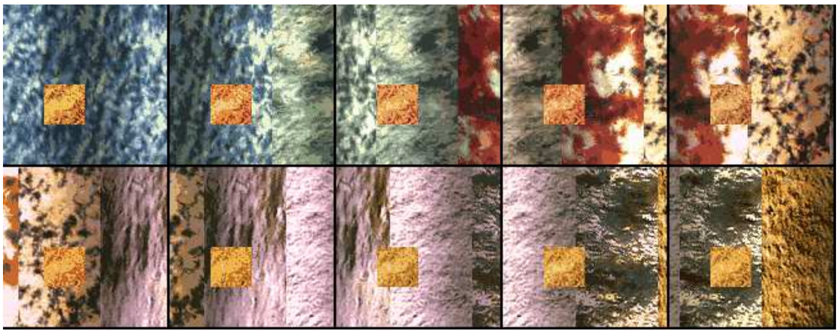

Fig. 6. Image sequence quantization by quantizing 3 frames in every batch.

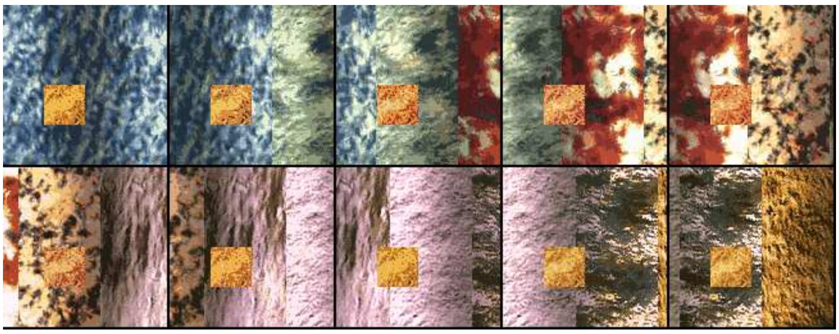

Fig. 7. Image sequence quantization by quantizing 3 frames in every batch and including both spatial weighting and time-frame weighting.

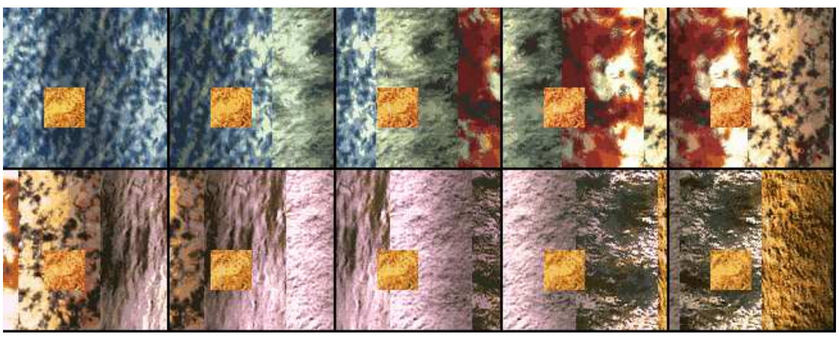

Fig. 8. Image sequence quantization by quantizing 3 frames in every batch and including spatial weighting, time-frame weighting and time-frequency weighting.

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