EXAMPLE-BASED BRIGHTNESS AND CONTRAST ENHANCEMENT

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ABSTRACT

Brightness and contrast heavily influence image visual quality; therefore, modern digital camera image processing pipelines typically include a brightness and contrast enhancement (BCE) algorithm that enhances visual quality by applying tone mapping to the image. There are many BCE methods published in the literature that are variations of histogram equalization (HE) and contrast stretching (CS). When tested on large image databases, there are always certain images where these algorithms fail because image content is very diverse and a fixed method fails to adapt to this large variation. Our paper addresses this problem. We have developed an example-based BCE algorithm that can adapt its behavior to different scene types by using training examples that are hand-tuned by human observers for optimal visual quality. Our algorithm models the optimal enhancement function from these training images using Principal Component Analysis (PCA). Then, given a new image, the algorithm predicts the best amount of enhancement by extrapolating from closest training images. We have performed perceptual evaluations that conclude that our algorithm effectively enhances brightness and contrast judged by human observers.

***Index Terms*—** Brightness contrast enhancement, training based, PCA modeling, scene adaptive, low complexity, real-time

1. INTRODUCTION

Brightness and contrast enhancement (BCE) algorithms enhance visual quality by applying tone mapping to the image. In this paper, we focus on BCE algorithms that apply a single tone map to the entire image, which we refer to as global brightness and contrast enhancement (GBCE). GBCE algorithms typically take the histogram of the image as input and calculate the best tone map for the image. There are many GBCE methods published in the literature. We particularly focus on those that are variations of histogram equalization (HE) and contrast stretching (CS) since these are well-suited for real-time implementations. A few examples of histogram-based algorithms are bi-histogram equalization [1] that reduces the mean brightness change, histogram low-pass filtering [2] [3] that reduces spikes in the histogram, gray-level grouping [4], and recursive sub-image/mean separate/separated and weighted HE (See [5]). Some algorithms decompose the input image into several sub-images, and then apply the classical HE process to each one [6], or introduce a specifically designed penalty term to adjust the level of contrast enhancement in addition to noise robustness, white/black stretching, and mean-brightness preservation that are incorporated into the cost function [7]. A retinex-theory based approach coupled with color correction was proposed in [8] and global tone mapping based on extending photographic practices of Ansel Adams is investigated in [9].

HE based GBCE algorithms distribute the pixels towards empty bins of the histogram, which typically improves the image by making the details in dark parts of the image to be more visible. CS, on the other hand, improves global contrast by making dark pixels darker and bright pixels brighter. A straightforward application of HE and CS can lead to unnatural images, so many variations have been proposed to properly adjust the amount of enhancement for a particular image, which is in general a very difficult problem since the optimal amount of enhancement has a complicated dependency on scene content. In addition to this, HE and CS may sometimes apply conflicting enhancements such as when the former is is trying to brighten a dark region to enhance visibility while the later may try to darken that same region to increase global contrast. In some images, brightening the dark parts might be the right enhancement, but in others humans may prefer making darks even darker to enhance global contrast. So, overall, the type and amount of the ideal enhancement is content dependent and is very difficult to consistently achieve for every image by using simple HE and contrast enhancement ideas. When we test traditional BCE algorithms on large image databases and judge the results by human observers, we easily find many failure cases where the enhancement is non-optimal. Actually, quite often the human observer prefers the original image over the enhanced one.

To address this challenging problem, we have developed an example-based GBCE algorithm that can adapt its behavior to different scene types by using hand-tuned training examples. These training examples are hand-tuned by human observers for optimal visual quality and specify the ideal amount of brightness and contrast enhancement for each scene type. Our algorithm models the optimal BCE function from these training images using Principal Component Analysis (PCA). Then, given a new image, the algorithm predicts the best amount of enhancement by extrapolating from closest training images. One strength of our algorithm is that if it is found to fail in certain specific scenes, we can always improve it by adding more hand-tuned examples from that particular type of scene. We have performed perceptual evaluations that conclude that our algorithm effectively improves the brightness and contrast of images judged by human observers.

In the following sections, we first describe our algorithm in detail. Then, we provide experimental results illustrating how our algorithm achieves good visual quality enhancement judged by human observers.

2. ALGORITHM OVERVIEW

In this section, we present the GBCE algorithm overview where we discuss the manual training procedure and enhancement prediction on a test image using a global tone-mapping.

2.1. GBCE Training Steps

For training our GBCE algorithm, we first collected a large and diverse set of sample images. The following steps describe our training procedure:

1. Compute the normalized 256 bin luminance histogram for each training image. We refer to this sum as Θ_H.
2. Determine a prototype set of the training database as follows:
   (a) For each image histogram in the training database, compute the distance to the histograms of the images that are in the prototype set and determine the minimum distance. We use sum of absolute differences as the distance measure. If prototype set is empty, add the current image to the prototype set and process the next image in the training database.
   (b) If the minimum distance is larger than a fixed threshold, we add this image to the prototype set and discard the image otherwise. Typically, we use a threshold of 0.8*Θ_H. We refer to the histograms in this prototype set as H_1, H_2, ..., H_n, where n is the number of prototype images.
3. For each image in the prototype set, manually tune a tone mapping curve that enhances the brightness/contrast of the image optimally according to user visual preferences. This manual tuning was performed by 18 people that included both visual quality experts and naive subjects, and their results were averaged to determine the optimal tone curve for the general population. Tone mapping curve is controlled by 7 control points located at $0, 25, 64, 128, 192, 225, 256$. User has the freedom to move the tone curve up and down at these control points to achieve the desired brightness/contrast enhancement. The result of tuning for each image will be a vector of length 7 that specifies the location of the tone mapping curve at the control points. This is shown in Figure 1. We call these vectors V_1, V_2, ..., V_n.

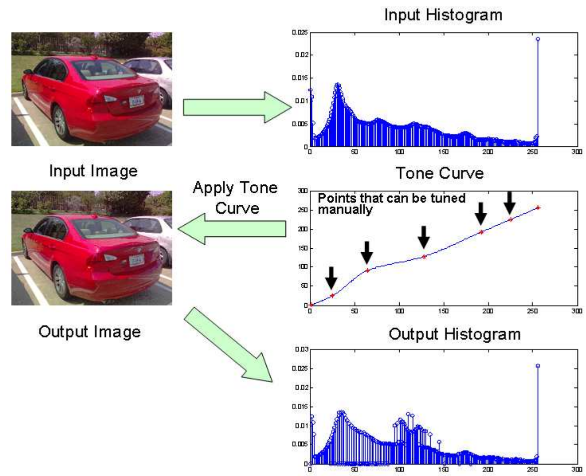

Fig. 1. Manual GBCE Tuning Interface

4. Finally, we apply principal component analysis to H_1, H_2, ..., H_n to reduce the dimensionality of the histograms in the prototype set. We refer to the eigenvectors that correspond to the largest eigenvalues as D_1, D_2, ..., D_z, where z is the number of eigenvectors that was selected to reduce dimensionality. The purpose of this step is to reduce memory requirements. The histograms and the tone curve pairs for the hand tuned images are arranged into matrices **H** and **T** respectively as shown in Equation 1. The size of these are $n \times 256$ since the number of histogram bins is 256, and the tone curve is also of the same length. We first compute the principal component vectors using singular value decomposition of **H** as shown in Equation 2. We chose a reconstruction error threshold of ϵ=0.5% in our experiments, computed the reduced dimension vector **D**=$\{D_1$, D_2, ..., $D_z\}$ as in Equation 3, and picked the first entry that satisfies the criteria. In our experiments z was 59, which means that the dimensionality of the histogram space is reduced from 256 to 59.

$$\mathbf{H} = \begin{pmatrix} \cdots & h_1 & \cdots \\ \cdots & h_2 & \cdots \\ \cdots & \vdots & \cdots \\ \cdots & h_n & \cdots \end{pmatrix} \mathbf{T} = \begin{pmatrix} \cdots & t_1 & \cdots \\ \cdots & t_2 & \cdots \\ \cdots & \vdots & \cdots \\ \cdots & t_n & \cdots \end{pmatrix} \tag{1}$$

$$\text{SVD}(\mathbf{H}) = USV^T \tag{2}$$

$$\Lambda = \sum(S) \leq max(\sum(S) * \epsilon) \tag{3}$$

Next, project all prototype set histograms on these eigenvectors to find the feature vectors, F_1, F_2, ..., F_n as in Equation 4. This concludes the training phase.

$$\mathbf{F} = \mathbf{D}\mathbf{H}^T \tag{4}$$

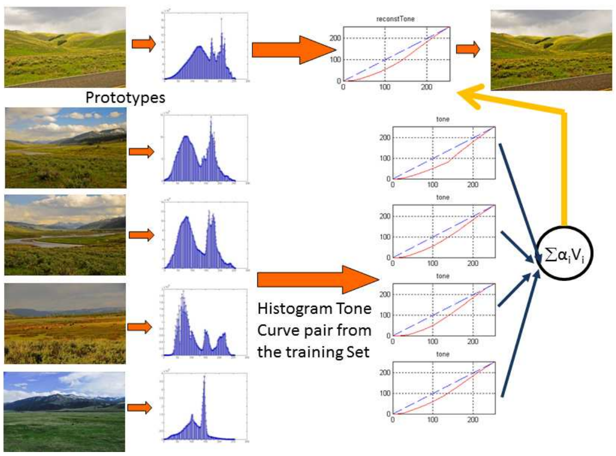

Fig. 2. GBCE Application on a Test Image

2.2. GBCE Application Steps

Given a new image that needs to be brightness/contrast enhanced, we apply GBCE as follows:

1. We compute the normalized 256 bin luminance histogram, H_{new} for this image.
2. We project H_{new} to the eigenvectors D_1, D_2, ..., D_z and then compute its distance to the feature vectors F_1,F_2, ..., F_n, using sum of absolute differences as shown in Equation 6, where the sum is over the columns c. Here **K** is the matrix with all unity entries. We rank these distances from the smallest to the largest denoted as d_1, d_2, ..., d_n.

$$\mathbf{PH} = DH_{new}^T \tag{5}$$

$$\mathbf{PSAD} = \sum_c (|\mathbf{F} - \mathbf{KPH}^T|) \tag{6}$$

3. From Equation 6, we compute $\mathbf{PSAD}_z$ and obtain the minimum distances of the four nearest neighbors (M) to H_{new}^T and their corresponding histogram indices from the training set. We picked $M = 4$ because it provided the best tradeoff in terms of quality and complexity for real-time implementation. The histograms that correspond to these M distances are the neighbors of H_{new} and can be used to estimate H_{new} by interpolation.
4. Using the corresponding tone points associated to the M histogram indices with minimum distance to H_{new}, we obtain the final tone points using a weighted summation as follows. Using the neighbor histograms with distances d_1 through d_M, we perform weighted interpolation to compute V_{new}, where V_{new} is the tone mapping curve that corresponds to H_{new}. The weights are computed such that the closest histograms (smallest distances) have the largest weight. We determine the weights as follows:

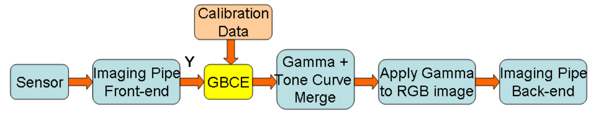

Fig. 3. GBCE in the Camera Imaging Pipe

   (a) Solve the following equation to determine k: (this ensures that weights will add up to one) (k/d_1)+(k/d_2)+...+(k/d_M) = 1
   (b) Next, we compute the weights as follows: $\alpha_1 = (k/d_1)$, $\alpha_2 = (k/d_2)$, ..., $\alpha_M = (k/d_M)$, where α_1 through α_M are the weights.
   (c) Estimate V_{new} as follows,

$$\mathbf{V}_{new} = \sum_{i=1}^{M} (\alpha_i V_i) \tag{7}$$

5. Determine the tone curve by interpolating V_{new} using bandlimited interpolation and apply it to the image to enhance brightness/contrast. This procedure is shown in Figure 2 for a outdoor landscape scene. As seen in the figure, we compute the four nearest neighbors to the luminance histogram of the test image and use the weighted summation of their corresponding tone curves to estimate the global tone curve that needs to be applied to the test image.
6. As shown in Figure 3, the GBCE block estimates the global tone mapping curve using the luminance histogram and the calibration data. The calibration data consists of all data that were pre-computed based on the manual training procedure explained in the previous section. The output of the GBCE block is the global tone curve, which is applied to the R, G, B planes. For YCbCr data, the tone curve is converted to a gain function and applied to Cb and Cr planes. In both cases, we make sure that we preserve the original color of the pixels during enhancement. This is ensured by maintaining the same $R/(R + G + B)$, $G/(R + G + B)$ and $B/(R + G + B)$ ratios before and after applying the tone curves.

3. RESULTS AND IMAGE QUALITY EVALUATION

We performed two types of experiments to evaluate the quality of our algorithm. In the first experiment described below, we quantitatively measure the ability of the algorithm to predict the optimal enhancement for a given image. In the second experiment, we ask human subjects to judge the visual quality of the enhanced images in a controlled perceptual experiment.

Enhancement Prediction Error Analysis: We evaluated the prediction error of the GBCE algorithm as follows. We started with a database of 900 images for which we had the hand tuned tone points. We divided this database into two sets: 600 images for training and 300 images for testing. We used 600 image training set to train the GBCE algorithm and

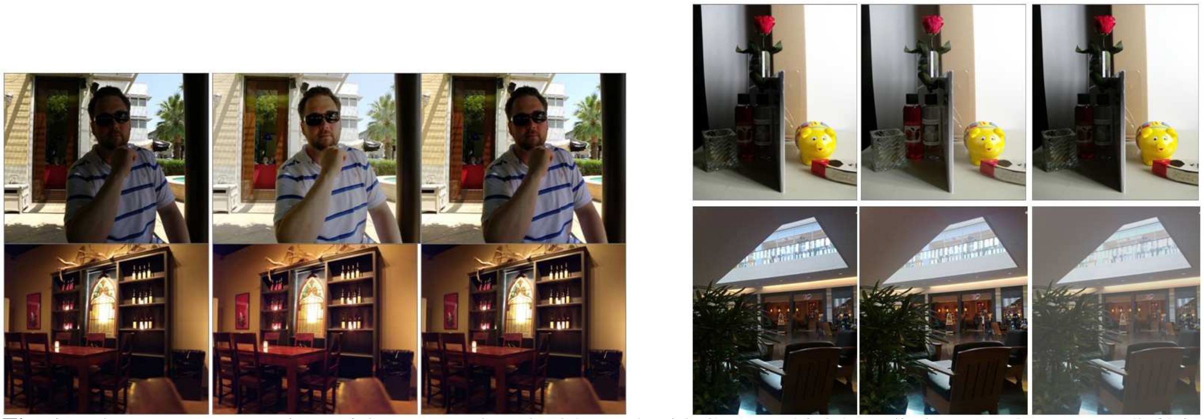

Fig. 4. Enhancement comparison of the proposed method (center) with CLAHE (right) applied to no-enhancement (left) images

then applied the GBCE algorithm to predict the tone points for the 300 test images. Then, we compared the 5 tone point prediction error values between the enhanced test images and the ground truth for each test image, and averaged over all 300 images. The average prediction error was 0.0165. As a comparison, we implemented a variation of adaptive histogram equalization called contrast limited adaptive histogram equalization $(CLAHE)$ [10] and compared its error with respect to the ground truth. The prediction errors are tabulated in Table 1 which shows that the error values of the proposed approach are much smaller compared to $CLAHE$. Prediction error for the proposed approach is 1.65%, whereas the error is 15.4% and 27.6% for $(CLAHE)$ and without any enhancement respectively. In Figure 4, we show the no enhancement images (left images), GBCE applied images (center images) and output of $CLAHE$ (right images) on four different scenes. In each of the images, the center image shows better visual image quality supporting the error prediction analysis. Next we present the perceputal quality experiment.

Perceptual Quality Evaluation: Subjective Evaluation is performed by displaying 3 versions of a single image side-by-side on two calibrated Apple Cinema HD 30 monitors in a low light (10 lux) environment to 23 human subjects [1] in a room without any ambient light. The proposed method was compared with no enhancement images and a competing algorithm based on adaptive histogram [10]. Images were labeled as 1.jpg, 2.jpg, etc. and monitors were labeled as A, B and C. Subjects were blinded to the algorithm and monitor configuration, and were requested to rate the quality of each image using the slider (scale: 0-10). The image set chosen for the evaluation consisted of 60 images comprising of normal scenes, scenes with high dynamic range (shadows with very bright regions), bright outdoor and cloudy/dusk outdoor, studio shots and low light indoors. The scores were converted to *z-scores* and a two-sided *t-test* comparison of the mean quality *z-scores* ranked the proposed algorithm as the best. The rank and the quality *z-scores* comparison is provided in Table 2 which shows a lower rank since it was consistently ranked better and a positive quality *z-scores* for the proposed method.

No Enhancement	CLAHE	Proposed Method
0.276	0.154	0.0165

Table 1. Prediction Error compared to the ground truth Manual tuning.

Quality z-scores	**CLAHE** -0.099350079	**Proposed Method** 0.101803789
Rank Sum	**CLAHE** 46	**Proposed Method** 23

Table 2. Quality z-scores and Rank comparison of the proposed method to CLAHE.

The algorithm was implemented on a $300MHz\ ARMA9$ processor and evaluated in real-time at HD resolution. The GBCE algorithm took $2ms$ and a memory of $5kB$ to generate the tone curve and the strength of the current approach is that it is not dependent on the image size since the input to GBCE algorithm is the luminance histogram and calibration data.

4. CONCLUSION AND FUTURE WORK

We have presented a GBCE solution that can be tuned separately for each specific scene type using training samples. This provides the flexibility for using the same algorithm for various applications such as video surveillance or mobile cameras by replacing the training images for that particular application. Then, given a new image, our method interpolates from past examples to decide the best brightness/contrast enhancement for the new image. This differentiates our method from all methods that have been proposed in literature. As part of the future work we are looking into local tone mapping and HDR tone-mapping based on similar techniques.

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