BRIGHTNESS PRESERVING VIDEO CONTRAST ENHANCEMENT USING S-SHAPED TRANSFER FUNCTION

Ke Gu, Guangtao Zhai, Min Liu, Qi Xu, Xiaokang Yang, and Wenjun Zhang

Institute of Image Communication and Information Processing, Shanghai Jiao Tong University, Shanghai, China
Shanghai Key Laboratory of Digital Media Processing and Transmissions

ABSTRACT

This paper presents an efficient perceptual model inspired efficient video contrast enhancement algorithm. We propose a S-shaped transfer function for image pixel values that effectively improves the perceived contrast while preserving brightness of the scene. The S-shaped transfer function has only one control parameter that can be adaptively chosen for different video contents, such as sports, cartoon, news, and landscape programs. Then, the input image brightness is further preserved, in order to maintain the perception of human visual system (HVS) to some special scenes, such as dark scene and seaside scene. Experiments and comparative study on VQEG Phase I test database demonstrate that the proposed S-shaped Transfer function based Brightness Preserving (STBP) contrast enhancement algorithm outperforms various histogram equalization based methods such as HE, DSIHE, RSIHE and WTHE, yet with much lower computational complexity.

Index Terms— Video contrast enhancement, S-shaped transfer curves, human visual system (HVS), video scenes, brightness preservation

1. INTRODUCTION

Contrast enhancement is an important research topic for image processing and computer vision. By smartly redistributing pixel values in an image, the image contrast can be drastically improved, as practiced by the traditional histogram equalization (HE) [1]. The fundamental objective of HE is to achieve the maximum entropy of the processed image so as to preserve image details. In brief, HE is conducted by adjusting pixel values according to the probability distribution of the input image pixel. Nowadays, the classical HE method has been widely employed in many image/video post-processing systems, because of its simplicity and effectiveness. However, since HE does not preserve the mean brightness and can therefore sometimes cause visible deterioration. More and more researchers in image processing tend to agree that HE is far from ideal as an image contrast enhancement algorithm.

Realizing this major drawback of HE, a large number of improved approaches by direct modification of HE to preserve the brightness have been proposed. Early methods BBHE [2] and DSIHE [3] by first decompose the input image histogram into dualistic sub-histograms, and then independently perform HE in each sub-histogram. The distinction is that the decomposition step of BBHE relies on mean brightness, while DSIHE using median brightness. To better preserve the mean/median brightness during sub-histogram separation, RMSHE [4] and RSIHE [5] adopt recursive operation to improve BBHE and DSIHE methods, respectively. In addition, some contrast enhancement techniques of higher computational load were recently developed based on the manipulation of dynamic range [6, 7, 8, 9].

Despite of the abundance of image contrast enhancement techniques, only very few studies have been devoted to video contrast enhancement during the last decade. Existing methods for video contrast enhancement can be divided into two categories. The first type of algorithms are the direct extension of image based methods. For instance, DSIHE, RSIHE and other brightness preserving algorithms can be applied to each frame. The WTHE algorithm [10] modifies image histogram by weighting and thresholding followed by HE. In the second type, [11] proposed a new and robust video contrast enhancement approach, by analyzing video streams and cluster frames that are similar to each other. More specifically, they extract key frames belonging to each cluster using eigen analysis and estimate enhancement parameters for only the key frame, and then use these parameters to enhance frames belonging to that cluster.

It is easy to imagine that video contrast enhancement demands lower computational complexity and higher temporal consistency. Those requirements rule out complicated method such as [6, 7, 8, 9, 11] as well as HE-based algorithms such as [1, 2, 3, 4, 5, 10] that may cause temporal luminance fluctuation due to the possible combination of neighboring histogram bins or the lack of brightness preservation. Our recent study indicates that a simple S-shaped transfer function is quite effective in perceptual contrast enhancement. The transfer function is controlled by only one free parameter that is tunable to different visual contents to customize and further improve the performance. Moreover, the S-shaped transfer function preserves the median brightness so it can be safely used in video sequence without spoiling the perception of human visual system (HVS) to special scenes.

The rest of this paper is organized as follows. Section 2 proposes the S-shaped Transfer function based Brightness Preserving (STBP) video contrast enhancement algorithm. In Section 3, experimental results using VQEG Phase I test database [12] are reported and analyzed. Finally, Section 4 concludes this paper.

2. THE PROPOSED ALGORITHM FOR VIDEO CONTRAST ENHANCEMENT

2.1. The S-shaped transfer curve

In our previous work [13] about subjective quality test of contrast-changed images, it was noticed that S-shaped transfer curve can significantly alter the perceptual contrast and a visual scene. In other words, the transfer curve are capable of improving the contrast of images to better match the preference of the HVS. For an input image I, the S-shaped transfer function used in this paper is defined as follows:

$$I' = \mathcal{S}(I, \boldsymbol{\pi}) = \frac{\pi_1 - \pi_2}{1 + exp(-\frac{(I-\pi_3)}{\pi_4})} + \pi_2. \tag{1}$$

Instead of tuning $\boldsymbol{\pi} = \{\pi_1, \pi_2, \pi_3, \pi_4\}$, we want to reduce the free parameters of the transfer function first. To solve all the four parameters, we will have to assume that the transfer curve passes several points $(\beta_i, \alpha_i), 1 \leq i \leq 4$. We require the curve to be symmetric with respect to the central brightness, namely the points $(\beta_1, \alpha_1) = (0, 0)$, $(\beta_2, \alpha_2) = (127.5, 127.5)$, $(\beta_3, \alpha_3) = (255, 255)$. We will set $\beta_4 = 25$ and let α_4 to be the only free parameter.

Then, we can calculate the optimal controlling parameters $\boldsymbol{\pi} = \{\pi_1, \pi_2, \pi_3, \pi_4\}$ by minimizing the following objective function

$$\boldsymbol{\pi}_{opt} = \arg\min_{\boldsymbol{\pi}} \sum_{i=1}^{4} |\alpha_i - \mathcal{S}(\beta_i, \boldsymbol{\pi})|. \tag{2}$$

With the computed model $\boldsymbol{\pi}_{opt}$, image I can be enhanced as

$$I' = max\{min[\mathcal{S}(I, \boldsymbol{\pi}_{opt}), 255], 0\} \tag{3}$$

where max and min operations limit the final pixel value I' in the bound of 0$\sim$255. And α_4 (denoted as γ later for simplicity) is the only controlling parameter to alter curvature of the transfer function.

2.2. The selection of model parameter

Since our S-shaped transfer curve has just one parameter γ. So the next step will be finding proper γ for different video contents. For video contrast enhancement, a same set of algorithm parameters should be applied to a cluster of frames in order to avoid temporal artifacts [11]. Therefore, we will use the same γ for a certain type of video contents.

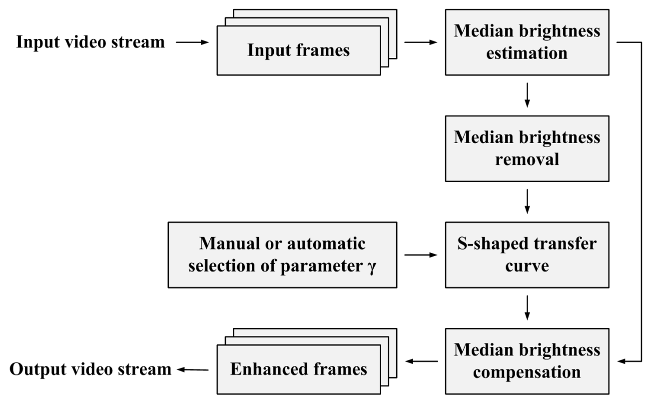

Fig. 1. The illustration of primary flowchart of STBP.

In our research, it was noticed that a small change of γ is enough for achieving dissimilar level of enhancement. So in this paper, we set γ as 9 or 12 for different types of contents. The larger the parameter γ, the less the level of contrast enhancement.

Parameter tuning of the algorithm operates in two modes: the universal mode and the manual mode. In the universal mode, the value of γ is constantly set as 12 without considering the type of video contents. The manual mode is to alter γ according to different types of video contents. We assume that sports- and cartoon-type of video programs have relatively higher original contrast and needs lower level of enhancement, i.e. larger γ. Meanwhile news- and landscape-type of programs can be enhanced more to to meet the audiences' expectation, i.e. smaller γ. The selection of γ used in this paper is as follows:

$$\gamma = \begin{cases} 9 & \text{if} \quad \text{news- and landscape-type programs} \\ 12 & \text{if} \quad \text{sports- and cartoon-type programs} \end{cases}. \tag{4}$$

Note that a wide set of parameter γ can be taken into consideration for more complicated classification of video program types.

2.3. The preservation of brightness

For the application of contrast enhancement techniques to TV programs in consumer electronics, some earlier works pointed out the significance of brightness preservation [2, 3, 4, 5]. However, as shown in Fig. 2-3, these enhancement approaches hardly produce satisfactory results because of the visually disturbing artifacts. As a matter of fact, the brightness preservation is more important for videos than for images, since the brightness deviation usually generates flickering artifacts, which are commonly seen in enhanced video sequences using traditional HE based methods.

So, in this work, median brightness subtraction and addition is adopted due to its simpleness and acquirement of maximum entropy [3].

2.4. The proposed STBP algorithm

Using the HVS based S-shaped transfer curve with one parameter and median brightness preservation, our STBP algorithm is defined as follows. For an input frame F_i, its median brightness is first computed by

$$m = median(F_i). \quad (5)$$

After that, F_i is modified based on the removal of the median brightness m:

$$F_i' = F_i - (m - 127.5). \quad (6)$$

We then perform Eq. (3) to improve the contrast of F_i':

$$F_o' = max\{min[\mathcal{S}(F_i', \boldsymbol{\pi}_{opt}), 255], 0\}. \quad (7)$$

where $\boldsymbol{\pi}_{opt}$ is estimated by letting the selected parameter γ into Eq. (2). At present, a higher-contrast image F_o' is obtained. The final result is produced by compensating the median brightness to F_o' so as to restore the brightness to its default value:

$$F_o = F_o' + (m - 127.5). \quad (8)$$

As illustrated in Fig. 1, the primary steps of the proposed STBP algorithm are presented.

3. EXPERIMENTAL RESULTS AND ANALYSIS

3.1. Experimental results

In this paper, we use VQEG Phase I test database [12] as a testing bed. This database totally involves 19 video streams with different contents. Three representative video sequences are selected, namely "Susie", "Moving graphic", and "F1 Car". Here, we assume that the first belongs to news- and landscape-type programs, and the other two correspond to sports- and cartoon-type.

Table 1. Median brightness of original frame(s) and various enhanced frame(s) of HE, DSIHE, RSIHE ($r = 2$), RSIHE ($r = 3$), WTHE ($r = 0.5, v = 0.5$), WTHE ($r = 1.0, v = 0.5$), STBP ($\gamma = 12$), STBP ($\gamma = 9$) methods. The results of Fig. 4 is computed by directly averaging the median brightness values among six successive frames.

Algorithms	Fig. 2	Fig. 3	Fig. 4
Original image	108	60	103
HE	109	77	109
DSIHE	107	57	94
RSIHE ($r = 2$)	109	68	99
RSIHE ($r = 3$)	108	62	103
WTHE ($r = 0.5, v = 0.5$)	119	168	176
WTHE ($r = 1.0, v = 0.5$)	84	49	99
STBP ($\gamma = 12$)	108	60	103
STBP ($\gamma = 9$)	108	60	103

Fig. 2-4 display various results of some mainstream contrast enhance methods. First, nine results of diverse algorithms are presented in Fig. 2. Clearly, Fig. 2 (f), (i) offer more real sensation of Susie's face, hair and etc, suggesting that the proposed STBP algorithm has generated better products than other popular contrast enhancement methods. Similarly, Fig. 3 also provides the same conclusion.

Next, we test the impact of γ on the results of our proposed algorithm. It is interesting to not that $\gamma = 9$ and $\gamma = 12$ have produced more desirable frame in Fig. 2 (i) and Fig. 3 (f) respectively. These results validate our proposed manual selection scheme of γ.

Further, we also compare four groups of successive enhanced frames extracted from the "F1 Car" video stream. It can be simply found in Fig. 4 (b)-(c) that the enhanced frames of RSIHE and WTHE suffer from flickering artifacts. In contrast, Fig. 4 (d) illustrates higher level of inter-frame consistency, indicating that our proposed algorithm has better processing results.

3.2. Performance analysis

The effectiveness of enhancing image/video using the S-shaped curves is not a purely experimental finding, but is supported by a recent finding in neurology [14]. It was suggested that the HVS uses the on-center and off-center cells and an accelerating nonlinearity to compute the subband skewness as an estimate of the perceptual surface quality. In practice, using S-shaped transfer curves, the proposed algorithm generates a longer positive tail, and according to [14], this induces higher level of perceived contrast. The median brightness of our method is exactly preserved by the "Median brightness removal" and "Median brightness compensation" steps, as illustrated by the median brightness values of original frame(s) and various enhanced frame(s) in Table 1.

Eventually, we have two remarks on the computational complexity. First, the optimization problem in Eq. (2) with two choices of the parameter γ and the associated S-shaped mappings can be solved off line and stored in a lookup table. So there are only four simple steps needed: median brightness estimation and removal, pixel value transfer using suitable S-shaped curve and brightness compensation. Second, the proposed algorithm works in a frame by frame manner for video contrast enhancement and therefore has very low requirement for memory and storage. The proposed algorithm is therefore very suitable for real-time video post-processing systems.

4. CONCLUSION AND FUTURE WORK

This paper proposed a fast and effective video contrast enhancement method (STBP) based on S-shaped transfer curves and median brightness preservation. There are two major contributions of our algorithm. First, the proposed algorithm is effective and efficient, suitable for real-time video contrast

(a) Original image (b)Output of HE (c) Output of DSIHE

(d) Output of RSIHE ($r = 2$) (e) Output of WTHE ($r = 0.5, v = 0.5$) (f) Output of STBP ($\gamma = 12$)

(g) Output of RSIHE ($r = 3$) (h) Output of WTHE ($r = 1.0, v = 0.5$) (i) Output of STBP ($\gamma = 9$)

Fig. 2. The example of "Susie" and its various enhanced frames.

enhancement. Second, the S-shaped transfer function is supported by neurological study of human eyes. Experimental results on video sequences from VQEG Phase I test database demonstrate the superiority and simplicity of the proposed STBP algorithm as compare to HE, DSIHE, RSIHE, and WTHE methods.

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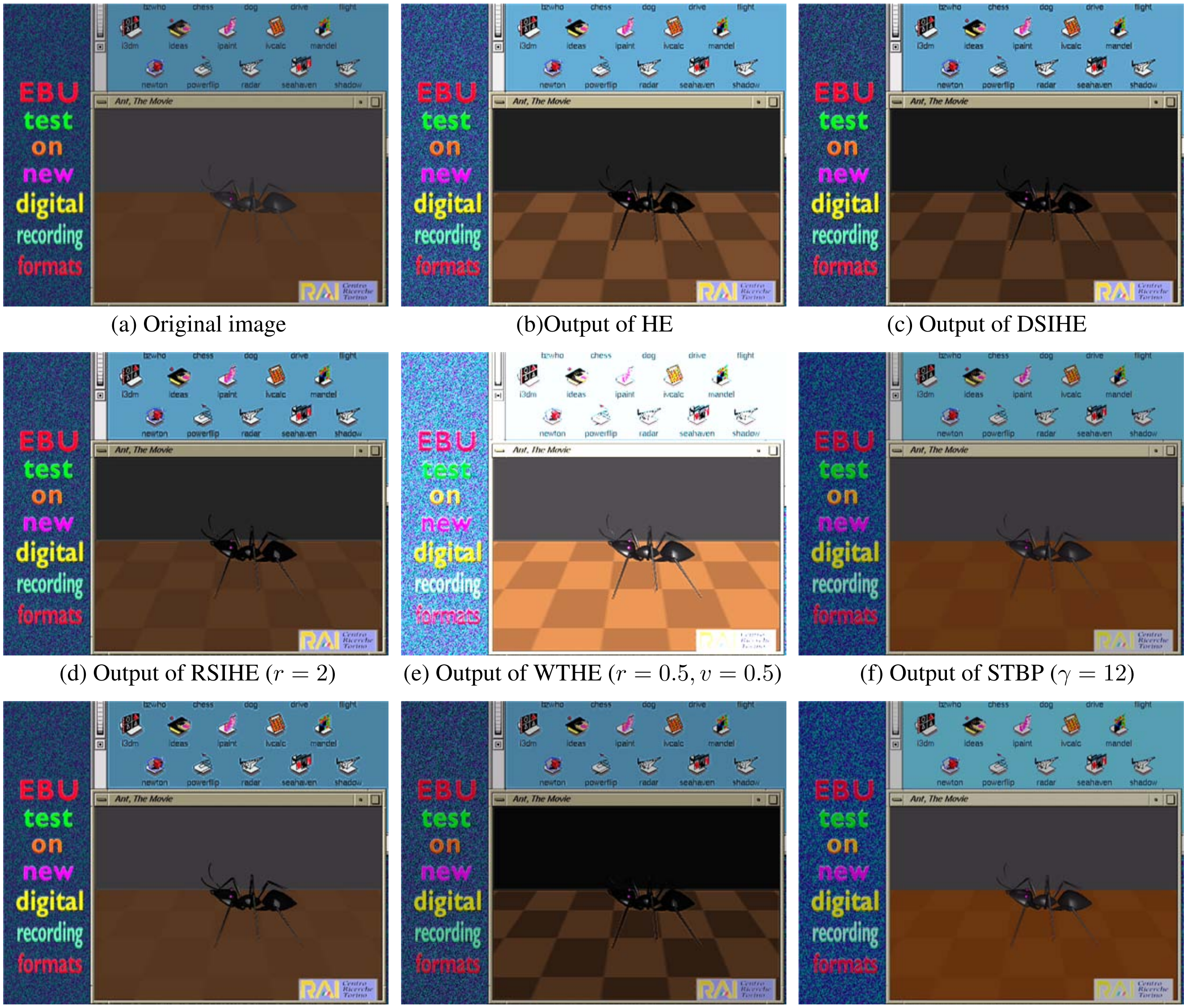

(a) Original image (b)Output of HE (c) Output of DSIHE

(d) Output of RSIHE ($r = 2$) (e) Output of WTHE ($r = 0.5, v = 0.5$) (f) Output of STBP ($\gamma = 12$)

(g) Output of RSIHE ($r = 3$) (h) Output of WTHE ($r = 1.0, v = 0.5$) (i) Output of STBP ($\gamma = 9$)

Fig. 3. The example of "Moving graphic" and its various enhanced frames.

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(a) Original image

(b) Output of RSIHE ($r = 2$)

(c) Output of WTHE ($r = 1.0, v = 0.5$)

(d) Output of STBP ($\gamma = 12$)

Fig. 4. The example of "F1 Car" and its various enhanced frames.