IMAGE ENHANCEMENT FOR IMPROVING FACE DETECTION UNDER NON-UNIFORM LIGHTING CONDITIONS

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ABSTRACT

A new wavelet-based image enhancement algorithm is proposed to improve performance of face detection in non-uniform lighting environment with high dynamic range. Wavelet transform is used for dimension reduction so that dynamic range compression with local contrast enhancement algorithm is applied only to the approximation coefficients. The normalized approximation coefficients are transformed using a hyperbolic sine curve which achieves dynamic range compression. Contrast enhancement is realized by tuning the magnitude of each coefficient with respect to its surroundings. The detail coefficients are also modified to prevent the edge deformation. Experimental results on the proposed algorithm show improvement on the performance of the Viola-Jones face detector when compared to other prominent enhancement techniques.

***Index Terms*—** Image Enhancement**,** dynamic range compression, local contrast enhancement, face detection.

1. INTRODUCTION

It is well known that human eyes perform much better than cameras when imaging real world scenes having high dynamic range that can span more than six orders of magnitude. Currently available imaging devices can measure only about three orders of magnitude. As a result the images captured in scenes with high dynamic range commonly suffer from poor visibility due to either overexposure causing saturation or underexposure resulting in low contrast dark images. This leads to poor representation of some of the important features in resulting images there by making it difficult to pick those by human eye or by computer vision algorithms.

Compressing the high dynamic range scene is a possible solution to handle the limited dynamic range (LDR) of the current devices. Various global histogram modification methods, such as gamma adjustment, logarithmic compression, histogram equalization and levels/ curves methods have been developed to implement this concept. Some features might be lost or some left un-enhanced when such methods are used and the result generally lacks the local contrast that contains significant image details. Progressive image enhancement techniques have been developed which not only accounts in compressing the dynamic range but also improving the local contrast thereby achieving high quality of vision.

MSRCR (Mutiscale Retinex with Color Restoration)[1-4], proposed by Rahman, *et al*, a widely cited image enhancement technique is a Retinex based algorithm that uses logarithmic compression and spatial convolution. It aims to synthesize local contrast enhancement, color constancy, and lightness/color rendition for digital color image enhancement. MSRCR works well with a large variety of images. IRME [5] (Illumaniance-reflectance model based nonlinear enhancement) is another novel technique proposed by Li et al. It is constituted by two separate processes viz. adaptive luminance enhancement and adaptive contrast enhancement to provide more flexibility and better control over image enhancement. IRME also produces good results for most natural images.

In this paper, we introduce a novel Fast and Robust Wavelet-based Dynamic Range Compression with Local Contrast Enhancement (WDRC) algorithm based on the principles introduced by MSRCR and IRME to improve the performance of face detection. Wavelet transform is used for dimension reduction such that a dynamic range compression with local contrast enhancement algorithm is applied only to the approximation coefficients which are obtained by low-pass filtering and down-sampling the original intensity image. The normalized approximation coefficients are transformed using a hyperbolic sine curve and the contrast enhancement is realized by tuning the magnitude of each coefficient with respect to its surrounding coefficients. The transformed coefficients are then de-normalized to their original range. The detail coefficients are also modified using the ratio between the original and enhanced approximation coefficients, followed by the inverse wavelet transform resulting in a low dynamic range and contrast enhanced intensity image. A color restoration process based on relationship between spectral bands and the luminance of the original image is applied to convert the enhanced intensity image back to a color image. The proposed algorithm is shown schematically in Fig.1.

2. ALGORITHM

The proposed enhancement algorithm consists of four main stages, three of which are applied in discrete wavelet domain:

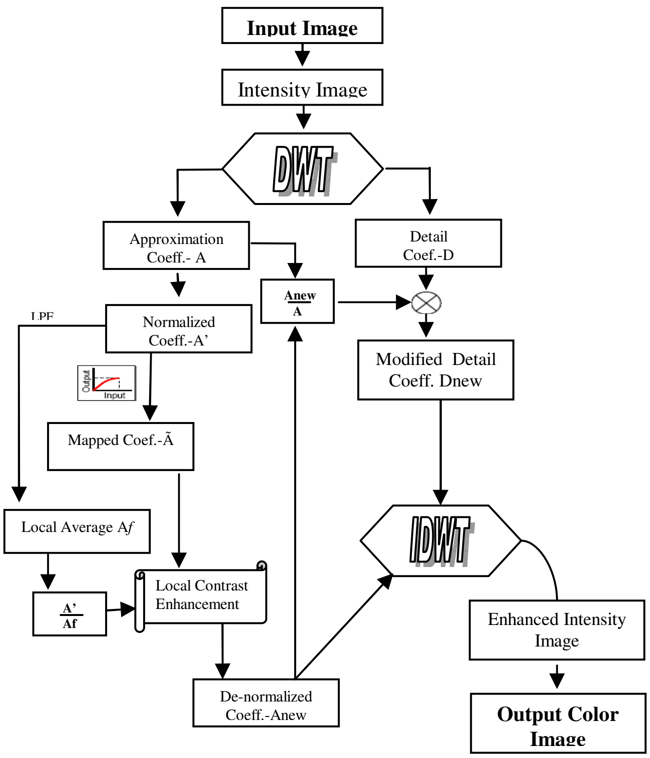

Fig.1. The proposed enhancement algorithm

1. Luminance enhancement via dynamic range compression of approximation coefficients.
2. Local contrast enhancement using averaged luminance information of neighboring pixels which is inherited to approximation coefficients
3. Detail coefficients modification.
4. Color restoration.

2.1. Dynamic range compression

For input color images, the intensity image I(x,y) is obtained by employing the following transformation:

$$I(x, y) = \max[r(x, y), g(x, y), b(x, y)] \quad (1)$$

where ***r***, ***g*** and ***b*** are the RGB components of color image in the RGB color space. This is the definition of the value (V) component in HSV color space. The enhancement algorithm is applied on this intensity image.

According to orthonormal wavelet transform, the luminance values are decomposed by Eq. (2):

$$I(x,y) = \sum_{k,l\in z} a_{J,k,l}\Phi_{J,k,l}(x,y) + \sum_{j\geq J}\sum_{k,l\in z} d^{h}{}_{j,k,l}\Psi^{h}{}_{j,k,l}(x,y) + \sum_{j\geq J}\sum_{k,l\in z} d^{v}{}_{j,k,l}\Psi^{v}{}_{j,k,l}(x,y) + \sum_{j\geq J}\sum_{k,l\in z} d^{d}{}_{j,k,l}\Psi^{d}{}_{j,k,l}(x,y) \quad (2)$$

where $a_{J,k,l}$ are the approximation coefficients at scale J with corresponding scaling functions $\Phi_{J,k,l}(x,y)$, and $d_{j,k,l}$ are the detail coefficients at each scale with corresponding wavelet functions $\Psi_{j,k,l}(x,y)$. While the first term on the right-hand side of (2) represents the coarse-scale approximation to *I (x , y),* the second term represents the detail component in the horizontal direction, the third and fourth represent detail components in the vertical and diagonal directions, respectively.

A raised hyperbolic sine function given in (4) which maps the normalized range [0, 1] of $a_{J,k,l}$ to the same range is used for compressing the dynamic range represented by the coefficients. We have chosen hyperbolic sine function for dynamic range compression since the function is 'two-sided'. This allows us to pull-up small coefficients and pull-down large coefficients to some extent at the same time. The dynamic range compressed coefficients at level *J* can be obtained by

$$\bar{a}_{J,k,l} = \left[\frac{\sinh(4.6248.a'_{J,k,l} - 2.3124) + 5}{10}\right]^{r} \quad (3)$$

where $a'_{J,k,l}$ are normalized coefficients given by (4) for 8-bit images and *r* is the curvature parameter that adjusts the shape of the hyperbolic sine function.

$$a'_{J,k,l} = \frac{a_{J,k,l}}{255\times 2^{J}} \quad (4)$$

In Fig. 2, hyperbolic functions with different curvature parameters are shown.

2.2. Local contrast enhancement

We used the centre/surround ratio introduced by Land [6] and efficiently modified by Jobson et al. [1] to achieve contrast enhancement. The center/surround ratio matrix is used as a variable gain by simply multiplying with the modified coefficients when the ratio is less than 1 and by applying inverse of this matrix as a power transform to the coefficients when the ratio is greater than 1. In doing such, the resulting images will not suffer from either halo artifacts or saturation caused by over-enhancement. The local average image represented by modified

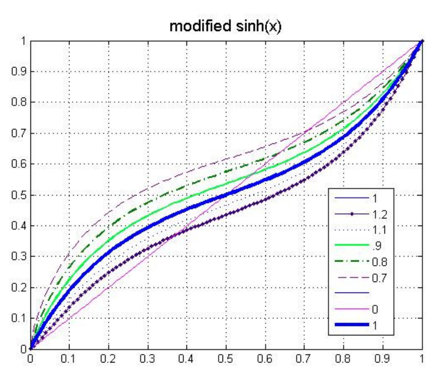

Fig.2. Raised hyperbolic sine function

approximation coefficients is obtained by filtering the normalized coefficients with a Gaussian kernel. The standard deviation (also called scale or space constant) of the 2D Gaussian distribution determines the size of the surround. The 2D Gaussian function $G(x, y)$ is given by,

$$G(x, y) = \kappa e^{\left(\frac{-\left(x^2+y^2\right)}{\sigma^2}\right)} \tag{5}$$

where κ is given by

$$\kappa = \frac{1}{\sum_x \sum_y G'(x, y)} \tag{6}$$

with $G'(x, y) = \exp(-\left(x^2 + y^2\right)/\sigma^2)$ and σ is the surround space constant. Surrounding intensity information is obtained by 2D convolution of (5) with image A', whose elements are the normalized approximation coefficients $a'_{J,k,l}$ given by (4) such as,

$$\begin{aligned} A_f(x, y) &= A'(x, y) * G(x, y) \\ &= \sum_{x'=0}^{M-1} \sum_{y'=0}^{N-1} A'(x', y') G(x - x', y - y') \end{aligned} \tag{7}$$

The ratio between A' and A_f determines whether the center coefficient is higher than the average surrounding intensity or not. If it is higher, the corresponding coefficient will be increased, otherwise it will be lowered such that the enhanced coefficients are obtained by,

$$A_{new} = \begin{cases} \bar{A}.R * 255 * 2^J & \text{for } R < 1 \\ \bar{A}^{-(\frac{1}{R})} * 255 * 2^J & \text{for } R > 1 \end{cases} \tag{8}$$

where, R is the centre/surround ratio and A_{new} is the new coefficient matrix which will replace the approximation coefficients $a_{J,k,l}$.

$$R = \left(\frac{A'}{A_f} \right)^d \tag{9}$$

Parameter d is used to tune the contrast strength with a default value of 1. Since using a single scale is incapable of simultaneously providing sufficient dynamic range compression and tonal rendition[1-4], different scale constants (e.g. small, medium, large) of the Gaussian kernel are used to gather surround information and the contrast enhancement process given by (5)-(9) is repeated for each scale. The final output is a linear combination of the new coefficients calculated using these multiple scales. This needs three times more calculations compared to using only one scale. Instead of using three convolutions, the same result can be approximated using a specifically designed Gaussian kernel. Such kernel which we name 'Combined-scale Gaussian (CG)' is a linear combination of three kernels with three different scales.

$$G(x, y) = \sum_{k=1}^{3} W_k \kappa_k \cdot e^{\left(\frac{-\left(x^2+y^2\right)}{\sigma_k^2}\right)} \tag{10}$$

where $W_k = \frac{1}{3}$. The CG kernel obtained using three scales (2, 40, 120) is shown in Fig.3.

2.3. Detail coefficient modification

Modifying the coefficients is very susceptible and may lead to undesired noise magnification or unpredictable edge deterioration such as jaggy edges. On the other hand the inverse wavelet transform with the modified approximation coefficients will also suffer from edge deterioration if the detail coefficient is not modified in an appropriate way. To meet this requirement, the detail coefficients are modified using the ratio between the enhanced and original approximation coefficients. This ratio is applied as an adaptive gain mask such as:

$$D^h{}_{new} = \frac{A_{new}}{A} D^h \qquad D^v{}_{new} = \frac{A_{new}}{A} D^v \qquad D^d{}_{new} = \frac{A_{new}}{A} D^d \tag{11}$$

where A and D are representing the approximation and detail coefficient matrices.

2.4. Color restoration

The RGB values $(r_{enh}, g_{enh}, b_{enh})$ of the restored color image are obtained by,

$$r_{enh} = \frac{I_{enh}}{I} r \qquad g_{enh} = \frac{I_{enh}}{I} g \qquad b_{enh} = \frac{I_{enh}}{I} b \tag{12}$$

where I is given by (1) and I_{enh} is the enhanced intensity image. Thus, color consistency between the original image and the enhanced image can be achieved.

3. RESULTS AND DISCUSSION

The proposed algorithm has been applied to process numerous color images captured under varying lighting conditions. From our observations we can conclude that the algorithm is capable of removing shades in the high dynamic range images while preserving or even enhancing the local contrast well. Besides, the produced colors are always consistent with the colors of the original images. Two of these results are shown in Fig.4.

The other advantage of the algorithm is its speed. Since the convolutions which take most of the processing time are only applied to the approximation coefficients, the processing time is reduced by more than two when compared to IRME which is known to be designed for real time video processing.

3.1. Improvement to face detection

The enhancement of the visual quality of digital images is usually applied to improve the performance of computer vision algorithms. Therefore, we used our proposed image enhancement technique as an image preprocessor for a face detection algorithm.

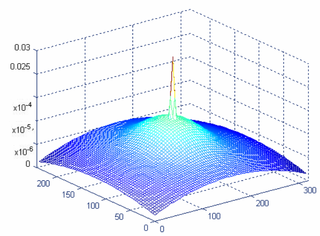

Fig.3. Spatial form of CG operator.

Fig.4. Color image enhancement results: Top: original, bottom enhanced images.

Figure 5. Face detection example: (a) original image, face not detected; (b) enhanced image by MSRCR, face not detected (c) enhanced image by IRME, face not detected (d) enhanced image by proposed algorithm with face detected.

The original face images and the enhanced face images produced by the proposed algorithm, MSRCR, and IRME were examined by the Viola-Jones [7] face detection algorithm to evaluate the detection rate change due to the improved visual quality of those images. 915 face images captured under uncontrolled indoor and outdoor environment were selected from FRGC database [8]. The results obtained from the detection experiments using the same threshold for all cases are given in Table 1. The enhanced results by the proposed algorithm give the best detection results and there is %2.187 improvement with respect to the detection rate of the original images. Two examples for the effect of the enhancement procedure for accurate face detection are shown in Fig.5.

	# of False Negatives (failed detection)
Original	34
MSRCR	28
IRME	17
Proposed	14

Table 1. Detection results

4. CONCLUSION

A wavelet based fast image enhancement algorithm which provides dynamic range compression preserving the local contrast and tonal rendition has been developed to improve the visual quality of the digital images. Experiments conducted for evaluating the improvement in face detection showed that proposed technique is more suitable as a preprocessor in face detection schemes when compared with MSRCR and IRME.

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