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GENERALIZED EQUALIZATION MODEL FOR IMAGE ENHANCEMENT

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Abstract- In this paper, we propose a generalized equalization model for image enhancement. Based on our analysis on the relationships between image histogram and contrast enhancement white balancing, we first establish a generalized equalization model integrating contrast enhancement and white balancing into a unified framework of convex programming of image histogram. We show that many image enhancement tasks can be accomplished by the proposed model using different configurations of parameters. With two defining properties of histogram transform, namely contrast gain and nonlinearity, the model parameters for different enhancement applications can be optimized. We then derive an optimal image enhancement algorithm that theoretically achieves the best joint contrast enhancement and white balancing result with trading-off between contrast enhancement and tonal distortion.

I. INTRODUCTION

Despite of the abundant literature on image enhancement, including those representatives listed above, two challenging problems for image enhancement are still not solved. First, how to achieve contrast enhancement while preserving a good tone. The contrast and tone of an image have mutual influence. Because of the complicated interaction, those algorithms merely aiming towards contrast enhancement or white balancing cannot provide optimal visual effect. Most, if not all, of current image enhancement systems divide white balancing and contrast enhancement into two separate and independent phases. This strategy has an obvious drawback: although tone has adjusted in the white balancing phase, contrast enhancement may undesirably bias it again. This trouble has been observed in many applications, e.g. the de-hazing algorithms in achieve contrast enhancement by increasing saturation of the image, but cause tonal distortion in some cases. It is easy to imagine that joint white balancing and contrast enhancement, is a more efficient solution towards overall quality enhancement.

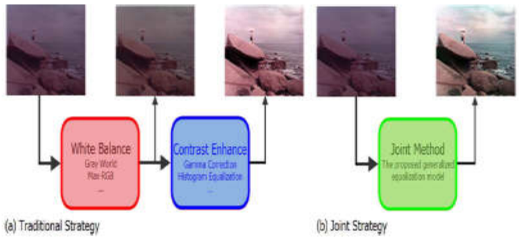


Fig (a) is the illustration of traditional image enhancement strategy. Fig (b) is the illustration of joint image enhancement strategy.

Second, how to theoretically relate different types of enhancement algorithms to each other. In this aspect, the work in [30] unifies spatial filtering based enhancement methods, including bi-lateral filter, non-local means filter, steering regression and so on, which has potential applications in image enhancement. However, the computational complexity of filtering based method is much higher than traditional histogram based method in most situations. In many cases, such as real-time video surveillance, the histogram based methods are still being widely used. Taking its significance in practical situations into consideration, finding a unified framework of histogram based methods is a meaningful work that may bring more inspirations to the image enhancement problem and facilitate future research. Although being originated from different applications, both of contrast enhancement and white balancing are essentially tone manipulation processes. In fact, it is noticed that almost all global algorithms of contrast enhancement and white balancing are based on histogram transform. Recently, on the concept of low-level visual information. However, this unified model does not take contrast into consideration, so it is limited to the application of white balancing. Wu [43] introduced a strict definition of expected context-free contrast and devised a method called Optimal Contrast-Tone Mapping (OCTM) to solve contrast enhancement problem by maximizing the expected contrast gain subject to an upper limit on tone distortion. OCTM is a promising solution for the intensity channel, but it does not elucidate the relationship between contrast and tone on the color channels.

In this paper, we will analyze the relationships between image histogram and tone/contrast of image, and establish a generalized equalization model. We will propose a series of definitions for context-free contrast, tone distortion and its nonlinearity, and clarify their relationships in terms of different parameters in the unified model. The generalized equalization model amalgamates histogram-based tone mapping algorithms in a generalized framework of convex programming and therefore is a joint strategy as shown in Fig.(b). Extensive experimental results show that the proposed method can be widely used in a series of enhancement applications with promising results.

II. IMAGE ENHANCEMENT

Image enhancement transforms images to provide better representation of the subtle details. It is an indispensable tool for researchers in a wide variety of fields including (but not limited to) medical imaging, art studies, forensics and atmospheric sciences. It is application specific: an image enhancement technique suitable for one problem might be inadequate for another. For example, forensic images/videos employ techniques that resolve the problem of low resolution and motion blur while medical imaging benefits more from increased contrast and sharpness. To cater for such an ever increasing demand of digital imaging, commercial softwares were released for users who want to edit and visually enhance the images. The purpose of this research is to evaluate if image enhancement techniques improve the visualization of these images and to study the effect of such an approach. Additionally, this work aims at contributing towards shortening the training period of the novice researchers in the lab.

A. Histogram Specification for Contrast Enhancement of Gray level Images

The first histogram equalization methods for image contrast enhancement were proposed in the early's seventies (Andrews et al 1972, Hall et al 1974). They were based on the principle that the visual contrast of a digitized image can be improved by adjusting its range of gray-level, so that the histogram of the output image is flat, *i.e.*, a uniform density can be specified from the output histogram. Hall et al (1974) introduces an idea of flattening the image histogram as given in information theory which states that the entropy of a signal is maximized when it has a uniform distribution property.

Histogram specification has been widely used for contrast enhancement in a variety of applications, such as medical image processing (Chang et al 1998, Kuwahara et al 1976, Pizer et al 1990 and Zimmerman et al 1988) and radar signal processing (Fuks et al 1998], due to its simple function and effectiveness. However, many of the proposed methods exist
have one drawback: the brightness of the processed image can be changed after the equalization is performed. This problem appears mainly due to the flattening property of the histogram equalization and it is rarely utilized in consumer electronic products such as TV, camcorders, video door phones and security video cameras. For consumer electronics, preserving the original brightness of the image may be necessary in order to reduce unnecessary visual deterioration.

B. Non-brightness Preserving Histogram Specification Methods

This section describes a set of methods which perform histogram equalization without taking into account of preserving the brightness of the processed image. Hummel (1975) showed that histogram equalization can be accomplished quite simply by using a look-up table which is applied to every point of the image. The transformation which comes closer providing a uniform density can be obtained from a scaled version of the cumulative density function, *i.e.*, the integral of the normalized original histogram. If this transformation has to be single valued, then gray-level bins of the original histogram can only be merged together but not broken up. Thus, if the original image has a histogram with large peaks, the transformed histogram will have only a very approximately flat histogram. Hummel et al (1977) proposed several techniques to obtain an exact equalized histogram, *i.e.*, an histogram with an exact uniform density. To achieve that, a multiple-valued transformation was defined, *i.e.*, different pixels with the same gray-level value having different output gray-levels. Kim et al (1999) proposed an image contrast enhancement method based on the piecewise-linear approximation of the cumulative density function (CDF) of the image. They actually proposed to approximate the computation of the CDF of an image. This approximate CDF makes methods based on histogram equalization faster and more suitable for real-time applications. Experiments showed that the accuracy of the approximated CDF with respect to the original one which is effective. The methods just described dealt with the problem of improving global contrast and were conceived to solve problems such as improper lightning conditions (excessive, poor, *etc.*) in the environment. On the other hand, local contrast enhancement methods which target the visibility of local details in the image were also proposed. Within this scope, adaptive histogram equalization (AHE) methods (Pizer et al 1984) are the most well known approach.

AHE works by finding local mappings from a pixel to its equalized version using local histograms. In its basic form, the AHE method consists of performing an histogram equalization at each pixel of the image based on its pixel neighborhood (its contextual region). An evaluation of the effectiveness of AHE for contrast enhancement in clinical computed tomography (CT) images of the chest is shown by Zimmerman et al (1988). Although AHE improves contrast locally, its computational complexity may not be acceptable for real-time applications.

Another disadvantage of the AHE method s is that they often over enhance the image, creating the so called contrast objects. Contrast objects are objects which were not visible in the original image. AHE can also be used to enhance noise in relatively homogeneous regions (Pizer et al 1987). However, image contrast enhancement by AHE methods often does not look natural (Stark et al 2000), and also amplifies noise.

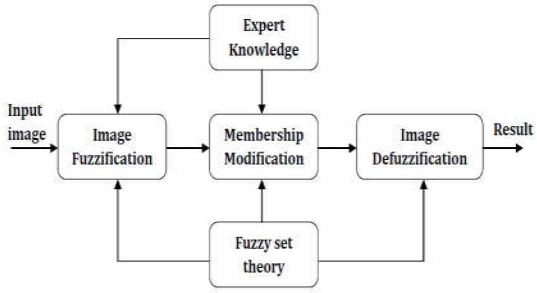
To overcome the drawback of noise amplification, a contrast limited AHE (CLAHE) method was proposed by Pizer (1990). The noise problem associated with AHE can be reduced by limiting the contrast enhancement specifically to the homogeneous areas of the images.

These areas are characterized by a high peak in the histogram associated with the contextual regions since many pixels fall inside the same gray-level range. A complete description and an implementation of this new method for real-time were presented by Reza et al (2004). A wavelet-multi16 scale version of CLAHE was also proposed by Jin et al (2001) and applied to improve the contrast of chest CT images. Aiming at reducing the number of operations required by the AHE method which makes its exact and original, conceived forms being not suitable for real time applications, various methods have been proposed in the last decade. For instance, in non-overlapped sub-block histogram equalization methods, the image plane is divided into a number of sub-regions and the pixels belonging to a particular sub-region are equalized using the local histogram of the sub region itself (Fuks et al 1998). Kim (1998) presented a system for enhancing contrast of image sequences using spatially adaptive histogram equalization with temporal filtering.

In that, a local enhancement is performed by block-overlapped histogram equalization followed by an efficient temporal filtering method for suppressing over-amplified noise. This local result is combined with the original image (a global result) to obtain the enhanced image. The authors claim that this system is practical for real-time applications. Kim (2001) developed alternative strategies which rely on partially overlapped sub-block histogram equalization (POSHE) and it achieves contrast enhancement rates similar to that of AHE but at the same time, it is capable of maintaining a fine visual quality to the image by getting rid of the blocking effect. Recently, Lambertiet al (2006) introduced a contrast enhancement algorithm which exploits efficient filtering techniques based on cascaded multiple-step binomial smoothing masks histogram equalization (CMBSHE) and achieved exactly the same results as POSHE.

III. FUZZY IMAGE PROCESSING

Fuzzy set theory is useful in handling various uncertainties in computer vision and image processing applications. Fuzzy image processing is a collection of different fuzzy approaches to image processing that can understand, represent and process the image . The representation and processing depend on the selected fuzzy technique and the problem to be solved. It has three main stages, namely, image fuzzification, modification of membership function values and defuzzification. Fig. shows the general steps involved in fuzzy-based image processing algorithms.



The coding of the image data (fuzzification) and decoding of results (defuzzification) are steps that make possible to process images with fuzzy techniques. The main power of fuzzy image processing is in the middle step, that is, the ability to modify or utilize the membership values according to the needs of the problem to be solved. After the image data are transformed from the spatial domain to fuzzy domain, appropriate fuzzy techniques modify or utilize the membership values. This can be fuzzy rule based approach, fuzzy clustering, fuzzy integration approach and so on . Soft computing algorithms proposed in this thesis for image restoration and enhancement uses fuzzy rule based approach for handling the membership values.

Fuzzy reasoning, also known as approximate reasoning, is an inference procedure whose outcome is a conclusion for a set of fuzzy if-then rules. The steps of fuzzy reasoning can be given as follows:

Input variables are compared with the membership function on the premise part to obtain the membership values of each linguistic label (fuzzification).

The membership values on the premise part are combined through specific fuzzy set operations to get firing strength (weight) of each rule.

Qualified consequent (either fuzzy or crisp) is generated depending on the firing strength.

Qualified consequents are aggregated to produce crisp output according to the defined methods (defuzzification). Fuzzy systems are made of a knowledge base and reasoning mechanism called fuzzy inference system.

A fuzzy inference system (FIS) consists of four functional components such as:

- **Fuzzification:** Transforms the crisp inputs into degrees of match with linguistic values.
- **Knowledge Base:** Consists of a rule base and a database. A rule base consists of a number of fuzzy if-then rules. A database defines the membership function of the fuzzy sets used in the fuzzy rules.
- **Fuzzy Inference Engine:** Performs the inference operations on the rules.
- **Defuzzification:** Conversion of fuzzy set to single crisp value.

There are two main types of fuzzy models: *Mamdani* and *Tagaki-Sugeno.* In the *Mamdani* type, both rule antecedent and consequent are in the form of membership functions. The model output is expressed in linguistic terms: it is a membership grade to a linguistic characteristic. In some cases, a linguistic output is desirable, thus, defuzzification can be avoided. In *Mamdani* models, defuzzification becomes necessary only when a numerical output is required. In *Tagaki-Sugeno* models, the rule conclusion is already a crisp value, and therefore, this model type does not require an explicit defuzzification procedure. Fuzzy-based soft computing algorithms proposed in this thesis were developed based on Tagaki-Sugeno fuzzy model type. Some of the important reasons that motivated us to use fuzzy-based soft
computing technique for solving image restoration and enhancement problems are as follows

- Fuzzy logic is a powerful tool for representing and processing human knowledge in the form of fuzzy if-then rules.
- Fuzzy techniques can manage the ambiguity and vagueness efficiently.
- It is flexible. With any given system, it is easy to manage it or layer more functionality on top of it.
- It is conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are very simple.
- It is tolerant of imprecise data and fuzzy reasoning builds this understanding into the process.

It is based on natural language. The basis for fuzzy logic is the basis for human communication. This observation underpins many of the other statements about fuzzy logic.

IV. THE PROPOSED MODEL

The aims of establishing the generalized equalization model include: 1) giving a unified explanation to white balancing problem and contrast enhancement problem; 2) providing an explicit objective function for these two problems and proposing a joint algorithm for them; 3) controlling the performance of the algorithm by as few parameters as possible. The proposed model is inspired by (7), (10). Although (7),(10) seem to be very different, if we regard the order of P_c and the norm of the objective function as two parameters, and , (7), (10) are rewritten in a generalized form:

$$\hat{\mathbf{s}}_c = \arg\max_{\mathbf{s}_c} \frac{1}{\left\|\mathbf{P}_c^{-\beta}\mathbf{s}_c\right\|_n}, \quad s.t. \quad \sum_{i=1}^{K} s_{ci} = L_c, \quad s_{ci} \geq d. \qquad \ldots\ldots\ldots(11)$$

Both (10) and (7) have interesting relationships with (11).When $n = 2$ and $\beta = 0.5$ (or $n = \infty$ and $\beta = 1$) maximum is reached when $s_{ci}/(p_{ci})^{\beta} = C$, which is equivalent (10). When $n = 2$ and $0 \leq \beta < 0.5$ (or $n = \infty$ and $0 \leq \beta < 1$), the solution would be smoother than that of (10). When $n = 1$ or $\to \infty$, the solution is equivalent to that of (7). Compared with traditional histogram equalization, (11) is more flexible, because the target histogram does not have to obey uniform distribution. Considering the fact that traditional histogram equalization often leads to over-enhanced results, relaxing the constraints of uniform distribution can suppress over-enhancement effectively. On the other hand, as long as $n > 1$and β in the suitable range, histogram of the enhanced image can avoid to be too sparse. As a result, we do not need additional constraints like OCTM does.

According to the analysis above, (11) provides a reasonable and unified definition with the objective function of contrast enhancement. We will further take white balancing into the model. Based on (4), (11), we formulate the generalized equalization model mathematically as follows.

$$\hat{\mathbf{s}}_c = \arg\min_{\mathbf{s}_c} \sum_{c=r,g,b} \left\|\mathbf{P}_c^{-\beta}\mathbf{s}_c\right\|_n, \quad s.t. \quad \sum_{i=1}^{K} s_{ci} = \frac{1}{e_c(\alpha)\sqrt{3}} \sum_{i=1}^{K} \tilde{s}_{ci}, \quad s_{ci} \geq d. \qquad \ldots\ldots\ldots\ldots(12)$$

Here, $\tilde{\mathbf{s}}_c$ is the original distance between adjacent intensity levels of the channel c . In generalized model, we set the upper bound L_c as the result of white balancing $1/e_c(\alpha)\sqrt{3}\sum_{i=1}^{K}\tilde{s}_{ci}$.

On the top of (12), we introduce two measures into generalized equalization model: the gain of expected context-free contrast and the nonlinearity of the transform from $\tilde{\mathbf{h}}_c$ to $\hat{\mathbf{h}}_c$, which are defined as

$$\mathbf{G} = \frac{\mathbf{p}_c^T\hat{\mathbf{s}}_c}{\mathbf{p}_c^T\tilde{\mathbf{s}}_c}, \quad \mathbf{NL} = \|\nabla(\hat{\mathbf{s}}_c - \tilde{\mathbf{s}}_c)\|_2 .$$

…….(13)

If $\tilde{\mathbf{s}}_c$ is homogeneous enough $\mathbf{NL} \approx \|\nabla\hat{\mathbf{s}}_c\|_2$, . The larger NL , the stronger nonlinearity of the transform. The nonlinearity of white balancing methods is close to 0. On the other hand, the contrast enhancement methods often have strong nonlinearity, which achieve visible enhancement of contrast. However, separate nonlinear transform of histograms of three channels may cause tone distortion. In the next section, we will theoretically prove that the proposed method, with a suitable configuration of parameters, can achieve a best trade-off between contrast enhancement and tone adjustment.

TABLE I
THE LIST OF IMPORTANT VARIABLES IN THE MODEL

Variables	Descriptions
$\tilde{\mathbf{h}} \in R^K$	The intensity levels of original image
$\hat{\mathbf{h}} \in R^K$	The intensity levels of enhanced image
$\tilde{\mathbf{s}} \in R^K$	The distance of adjacent intensity levels of original image
$\hat{\mathbf{s}} \in R^K$	The distance of adjacent intensity levels of enhanced image
$\mathbf{p} \in R^K$	The probability of intensity level
$\mathbf{P} \in R^{K\times K}$	The diagonal matrix of $\mathbf{p}$
L	The upper bound of intensity
d	The lower bound of distance
$\mathbf{e}(\alpha)$	The estimated light source for original image
α	The parameter of color constancy
β	The parameter of nonlinearity
n	The parameter of norm
$\mathbf{G}$	Contrast Gain
$\mathbf{NL}$	Nonlinearity of transform

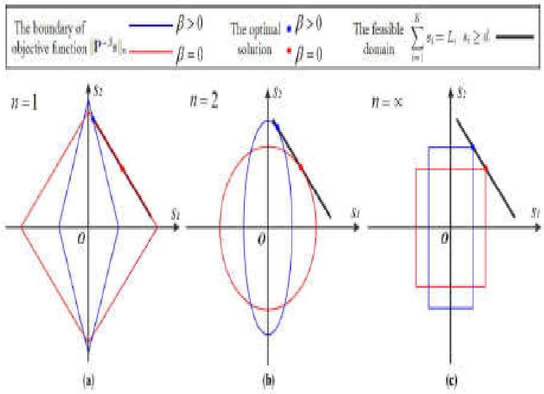


Fig. In each sub-figure, the thick black line represents the feasible domain of Eq. (12); the red and blue wireframes show the boundaries of the objective function of Eq. (12) which correspond to the $\beta = 0$ and $\beta > 0$ situations respectively; the red and blue points are the optimal solutions corresponding to the $\beta = 0$ and $\beta > 0$ situations respectively. The parameter in (a), (b), (c) is 1, 2 and ∞ respectively.

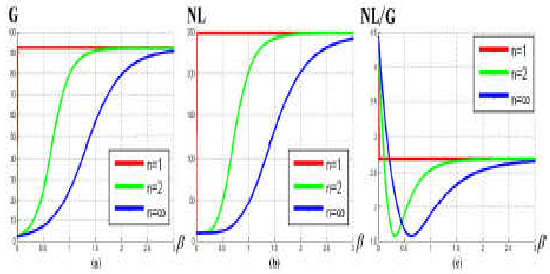


Fig. . Figure (a) gives the curves of contrast gainwith the increase of . Figure (b) gives the curves of nonlinearity of transform with the increase of β . Figure (c) gives the curves of the ratio of NL_n to G_n ,n=1,2,.∞ . The red, green and blue curves corresponding to n=1,2,….∞, respectively.

CONCLUSION

In this paper, we analyzed the relationships between image histogram and contrast/tone. We established a generalized equalization model for global image tone mapping. Extensive experimental results suggest that the proposed method has good performances in many typical applications including image contrast enhancement, tone correction, white balancing and post-processing of de-hazed images. In the future, besides global image enhancement, we expect to unify more local image enhancement methods into the model through local image feature analysis.

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