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Infrared image enhancement using adaptive trilateral contrast enhancement ☆

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ABSTRACT

A novel contrast enhancement method called adaptive trilateral contrast enhancement (ATCE) method is presented. Unlike conventional methods which exaggerate the contrast difference between fore- and background of an image as a means to improve image visual quality, ATCE method provides a multifaceted approach which involves enhancement of both image contrast and subtle image details. The designation of "trilateral" is derived from the working principle of ATCE which utilises three different types of image characteristics, namely, contrast, intensity and sharpness, to concurrently enhance the visual quality of an image. In the experiment on a set of infrared thermal images captured under low-light night time environment, ATCE is evaluated and compared to some existing contrast enhancement methods. The quantitative experimental results show that ATCE significantly surpasses other existing methods on the measure of enhancement by entropy.

1. Introduction

Conventional histogram equalisation (CHE) is considered as one of the principal image processing algorithms that has been traditionally used to improve the image contrast quality through rescaling the dynamic range and histogram distribution of a greyscale image [5]. For CHE, a uniform transfer function is often adopted to redistribute the histogram counts, forcing the histogram distribution to be flatten out and occupied a wider dynamic range as a means of exaggerating the contrast differences between the fore- and background of an image [2,14].

Kim suggested a bi-histogram equalisation model, called the brightness preserving bi-histogram equalisation (BBHE), to reduce the aforementioned shortcomings of HE [7]. In 2003, Chen and Ramli [4] suggested a recursive approach for BBHE, where the decomposition of histogram distribution is performed recursively within each sub-histogram based on their respective mean brightness level. It is called the recursive mean separate histogram equalisation (RMSHE) method. Although the recursive approach of RMSHE provides a flexible means of monitoring the degree of over-equalisation defect, yet this approach has been overly emphasising on keeping the mean brightness value. For infrared thermal images with low image contrast, excessively emphasising on preserving the input mean brightness through higher recursive level will inevitably lead to inadequate enchantment results. To overcome this dilemma, a hybrid of bi-histogram and plateau histogram models was proposed [11].

Vickers [16] suggested a plateau histogram model, known as plateau histogram equalisation (PHE), as an attempt to reduce the noise amplification and over-equalisation artefacts during the histogram equalisation process. As the plateau threshold value for PHE is empirically chosen, the practical usage of PHE method is rather limited due to the vast differences in nature of greyscale images and the requirement of human intervention which may incur unwanted cognitive bias during the contrast enhancement process. To resolve this shortcoming, Liang et al. [6] proposed the adaptive double plateau histogram equalisation (ADPHE) to derive the value of plateau thresholds based on the characteristics of input images.

Adaptive histogram equalisation (AHE) is a localised model of HE, where the image pixels are contrast-enhanced by local transfer functions that derived from defined sub-image plots. Despite the stronger contrast enhancement effect offered by AHE, the practical usefulness of AHE is rather limited as this form is slow and computational intensive; the number of times that the local equalisation process should be repeated is equivalent to the total amount of pixels available in the image. Moreover, it may be inappropriate to transform pixels within low-contrast region with a full histogram equalisation mapping as the local histogram distribution for highly homogenous (or low contrast) region is often severely skewed, thus very susceptible to over-equalisation artefact [15]. To overcome such deficiencies, an

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improved version of AHE that featured with contrast limitation and fast computational time, known as the contrast-limited adaptive histogram equalisation (CLAHE), was proposed [13].

Several types of conventional contrast enhancement methods with different nature of working principles have been discussed. In this paper, the constraints of aforementioned contrast enhancement methods when applied on low contrast infrared thermal images is addressed. Therefore, a novel approach is developed as a solution for these drawbacks.

2. Research and methodology

The proposed adaptive trilateral contrast enhancement (ATCE) is a novel variation of image contrast enhancement techniques, which extends the model of conventional histogram equalisation by combining it with the concept of image filtering to provide a multifaceted contrast enhancement algorithm. The "trilateral" refers to the three different types of image characteristics, namely, the image contrast (IC), image sharpness (IS) and image intensity (II), to concurrently enhance the visual quality of an image. Such multifaceted enhancement can be achieved by first manipulating the contrast of image to improve the overall image visual quality, followed by fine-tuning the intensity and sharpness of image to further preserve and magnify the subtle image details.

2.1. Image contrast (IC) manipulation

For a greyscale image, the image contrast can be defined as the perceivable grey intensity differences that discriminate objects from the background of an image [9]. In ATCE, the concept of plateau histogram equalisation (PHE) is adopted as the underlying principle for image contrast manipulation due to its simplicity and flexibility, as elaborated earlier. However, unlike conventional PHE, the image contrast manipulation in ATCE utilises two plateau threshold values; an upper plateau threshold value is deployed to restrain the severity of over-equalisation and noise amplification artefacts, while an additional lower plateau threshold value is used to prevent subtle image details from overwhelming by drastic contrast gain. The proposed image contrast manipulation consists of three main stages: image segmentation, local histogram equalisation and image reconstruction.

During the image segmentation process, the input image is divided into a defined number of non-overlapping and equally-sized sub-images. By regionally isolated the input image, each sub-image is allowed to be enhanced independently based on their own respective local histogram distribution, thus capable of achieving stronger contrast with least influence from non-adjacent regions with vastly different nature of grey intensities distribution. Furthermore, such procedure allows the subtle image details to be well-preserved as they are less likely to be engulfed during the contrast enhancement process; the magnitude of contrast gain is ranked proportionally among the pixels within close proximity, rather than against entire image.

For histogram equalisation, one of the main concerns is the effect of over-equalisation due to inequality of histogram distribution. The inequality of histogram distribution is often referred as a phenomenon where highly dense histogram counts are being populated within a limited number of grey intensity levels, causing an undesirable drastic brightness change during equalisation process as the contrast gain values given to each grey intensity level are scaled proportionally according to the density distribution of histogram counts. However, rather than using an arbitrarily selected threshold to globally restrict the height of histogram distribution, the proposed image contrast manipulation attempts to study the nature of such inequality to adaptively derive an optimal threshold value to remodel the histogram distribution. A good general measure for analysing the inequality of distribution is known as the Lorenz curve.

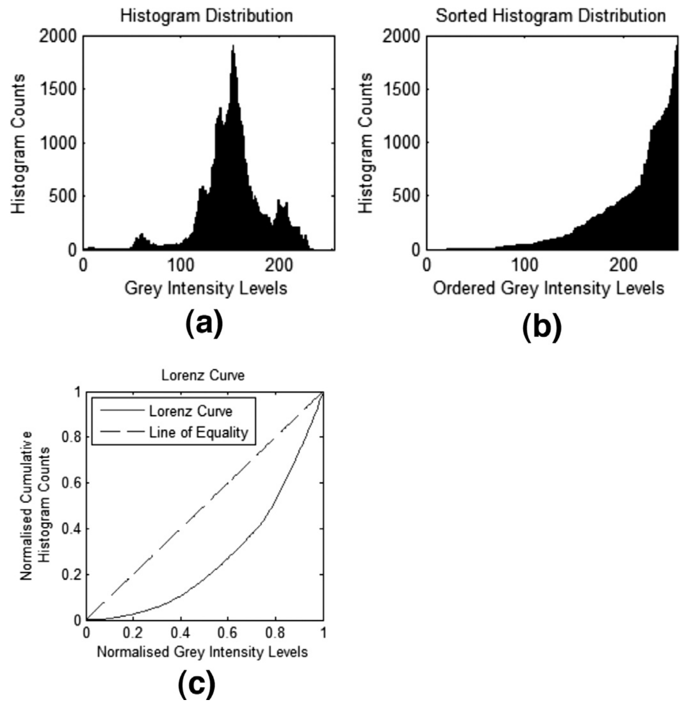

Fig. 1. Illustration of Lorenz curve. (a) Histogram distribution, (b) sorted histogram distribution, and (c) the corresponding Lorenz curve.

The Lorenz curve is a statistical model first developed in economics to represent the proportionality or inequality of a distribution. The proportionality of distribution is illustrated by a curved line, or the Lorenz curve, where points along the curved line represent the cumulative proportion of distribution assumed by each individual subject against the cumulative distribution of entire population; the degree of inequality is defined by the curvature of Lorenz curve, with a steeper curve denotes a higher degree of inequality, and vice versa. Meanwhile, a hypothetical straight diagonal line, known as the line of equality, is often drawn along with the Lorenz curve to represent a uniform distribution where each subject has the same proportion as rest of the population. Fig. 1(c) illustrates an example of a typical Lorenz curve.

With reference to the plotted Lorenz curve in Fig. 1(c), the measure of inequality can be computed by calculating ratio between the "area of concavity" (area of difference between Lorenz curve and line of equality) and the "area-under-graph" (total area under line of equality). The measure of inequality, or more commonly known as the Gini coefficient, can be written as

$$g = \frac{\sum_{k=0}^{K-1} \{cdf_e(I_k) - cdf_c(I_k)\}}{\sum_{k=0}^{K-1} cdf_e(I_k)}; \quad k = 0, 1, 2, \ldots, K-1, \tag{1}$$

where g represents the Gini coefficient; $cdf_e(I_k)$ and $cdf_c(I_k)$ denote the CDF for line of equality and Lorenz curve at ordered grey intensity level, I_k, respectively. K is the number of grey intensity levels, typically set at 256 for greyscale image. Based on Eq. (1), the plateau threshold values used to re-model the local histogram distribution can be derived as

$$T_u = (1 - g)h_{\max} + gT_l; \quad 0 \le g \le 1, \tag{2}$$

$$T_l = n/K, \tag{3}$$

where T_u and T_l denote the upper and lower plateau threshold values, respectively; $h_{\max}$ represents the highest histogram counts; n