A short review on classical and recent contrast enhancement and exposure correction techniques

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Abstract. Contrast enhancement and exposure correction techniques are important in many applications that rely on images captured by cameras. This paper reviews such techniques. Focus is made on histogram based and learning based methods. It was observed that newer methods attempt to overcome drawbacks of previous methods, but to achieve this they often reduce the enhancement capability and add computational load. It was also observed a growing use of learning based methods in this field, specially methods using deep convolution neural networks (CNNs). A conclusion of this review is that newer methods are in general not replacements to previous methods; each method has its advantages and drawbacks and is more appropriate to specific problems and applications.

Keywords. Image processing, contrast enhancement, exposure correction, histogram equalization, deep learning.

1. Introduction

Two of the most frequent problems affecting the use of raw images captured by digital cameras are the presence of under and over exposition and low contrast. Multiple factors make these problems almost unavoidable to some extent. First, if the real scene irradiance varies too much, containing both dark to mid tone and very bright areas, then traditional digital cameras will not be able to register the full dynamic range in a single image, no matter the choice of the exposure time. Second, physical elements in the scene, such as fog and light dispersion in the air, may prevent a faithful registration of the contrast and colors of the surfaces in the scene. Third, the devices used to capture the images are imperfect and tend to generate distortions.

In order to solve these problems in an image already taken, exposure correcting and contrast enhancing algorithms are needed. Contrast enhancing algorithms are also useful to make elements more visible in images, so as to improve the performance of computer vision algorithms (e.g., segmentation, object recognition, edge detection etc.) or to facilitate human observations in specific kinds of image (e.g., medical images, satellite images, astronomic images, micrographs etc.) [1]. This second use differs from the first by not necessarily requiring naturalness preservation.

The literature of exposure correction and contrast enhancement is quite vast. And so is the number of different applications and problems that require these algorithms. As a consequence, no algorithm will be the most appropriate in every application or problem.

The problems of defective exposure and low contrast are directly related. By correcting the exposure problems, the contrast will likely be improved, and vice versa. That happens because under and over exposed regions have low contrast.

This paper reviews the state-of-the-art algorithms for exposure correction or contrast enhancement. Since there is a very large volume of algorithms in this category, the review is far from comprehensive. Focus is made on the histogram based and learning based methods. It was observed a growing use of learning based methods in this field, specially methods using deep convolution neural networks (CNNs). Such heavy learning based methods have accomplished impressive tasks, but they also have drawbacks, and thus analytical or exact approaches will continue to be used and developed in the foreseeable future. At the end of the paper, the conclusions of the review are summarized and discussed.

2. Histogram based methods

This section reviews some of the histogram based contrast enhancement or exposure correction algorithms. Since the literature of histogram based methods is very large, a selection was made among the most either classical, recent or relevant algorithms.

2.1 Classical algorithms

The level of contrast of a given region of an image is related to the histogram of the intensities of the pixels within this region. If the histogram is narrow, then there is little variability and the contrast is low. If the histogram spreads well over the full intensity range, then the contrast is high. Hence, by stretching the histogram of an image, the contrast is expected to improve.

The most 'spread' configuration that the histogram can have, which by the principle above would correspond to a very good contrast, is a uniform (flat) shape, where all levels occur with the same frequency. It can be shown that this is the configuration with maximum entropy of the image levels [2], and then an image of a given scene with uniform histogram is expected to carry more information than an image of the same scene and size with a non-uniform histogram.

Viewing the image intensities as samples of a random variable, the normalized histogram of intensities of an image gives the discrete probability density function (PDF) of the intensities. The cumulative sum of the normalized histogram gives the discrete cumulative distribution function (CDF) of the intensities. From statistics theory, applying the CDF of a continuous random variable to the random variable will maps it into a new variable with uniform distribution. This is approximately true for the discrete case. Hence, applying to the image the CDF of its intensities (obtained from its histogram) will spread the histogram of the image across the full pixel value range, thus increasing contrast. This method is known as global histogram equalization (GHE), or simply histogram equalization (HE).

GHE is able to improve contrast adequately for some images, but it has some limitations. First, the transformation does not adapt to the needs of each region; it is the same for every pixel. Second, the output image histogram will not be exactly uniform, containing in many cases a "spiky" aspect that is accompanied by the production of artificial edges (staircase effect). Third, uniform is not necessarily the best target shape for the histogram of a image, and force it frequently will over enhance the contrast. Despite these limitations, GHE has a very low cost and is fully automatic, not requiring parameter adjustments. Besides, it is the starting point for more sophisticated algorithms.

Local Histogram Equalization (LHE) attempts to overcome the first limitation of GHE mentioned above. This method moves a window through the image and executes histogram equalization for each position, using in the calculation only the pixels inside the window, and updating only the central pixel [3].

Since a histogram equalization is performed for each pixel, LHE is very costly. Adaptive Histogram Equalization (AHE), another local version of GHE, avoids this cost by dividing the image into rectangular tiles, obtaining the HE transformation for each tile separately and computing the output values with a bilinear interpolation of the values resulting from the transformation functions obtained for the neighbor tiles.

One of the main drawbacks of LHE and AHE is that they over enhance the contrast, specially in regions that naturally have little contrast (e.g., a clean sky region). Pizer [4] proposed to overcome this problem for the AHE case by clipping the obtained histograms, which limits the maximum slope of the transformations computed for each tile, originating the method named Contrast Limited Adaptive Histogram Equalization (CLAHE).

From the ability to obtain a transformation that flattens the PDF of a random variable, comes automatically the ability to map the variable into a new variable with any target PDF. The reason is that, given the target PDF, its CDF is the transformation that flattens the PDF of a variable distributed by the target PDF, and then the inverse of such CDF maps a variable with uniform PDF into a variable with the target PDF. Hence, the composition of the CDF of the original random variable with the inverse of the CDF of the target PDF is the transformation that maps the original random variable into a new variable distributed by the target PDF. Using the histograms as PDFs, we thus obtain a method to specify the histogram of a image. The resulting algorithm is called Histogram Matching (HM) or Histogram Specification.

All these algorithms are extended to color images typically by representing the image in a color system that separates luminance information from color information (e.g. HSV and L*a*b*) and applying the algorithm to the luminance channel only — here, "luminance" is used in a broad sense, and can have different physical interpretations depending on the color system. Sometimes the saturation channel is also equalized. If a histogram equalization based algorithm is applied to the RGB components directly and separately, the color balance of the image will change, and unnatural colors may appear. In some applications, however, the image already has a bad color balance, and applying histogram equalization on the RGB channels can improve this balance. In others, there is no need to preserve the color balance and naturalness, and then applying histogram equalization on the RGB channels is reasonable.

2.2 Subsequent improvements

Kim [5] observed that one of the weaknesses of classical GHE is that it does not preserve the mean brightness of the image, which leads to distorted results. He then proposed a transformation based on histogram equalization that does not change the gray level equal to the mean brightness of the original image, which he calls Brightness Preserving Bi-Histogram Equalization (BBHE). Let μ be the mean brightness of the original image and $\mathcal{S}_>$ (resp., $\mathcal{S}_<$) the set of pixels with level greater (resp., smaller) than μ. BBHE applies HE to $\mathcal{S}_<$ and $\mathcal{S}_>$ separately and scales the outputs to $[0, \mu]$ and $[\mu, 1]$, respectively. In cases where GHE changes the mean brightness too much, BBHE provides dramatically more natural results.

Although BBHE does not change the pixels with level equal to the mean brightness of the original image (the result of the transformation for a pixel with value μ is μ), the mean brightness of the output image will *not* be equal to μ in general. Chen and Ramli [6] proposed a modification of BBHE where the threshold that defines $\mathcal{S}_<$ and $\mathcal{S}_>$ is not set to μ, but instead is set to a value that minimizes the AMBE (Absolute Mean Brightness Error) — which consists in the absolute difference between the means of the output and input images. The results showed a performance comparable to BBHE in cases satisfactorily enhanced by BBHE, and better than BBHE in some cases not handled adequately by BBHE.

Huang, Cheng and Chiu [7] proposed to enhance the image by applying an adaptive gamma correction, where the gamma correction parameter γ is computed using the smoothed CDF of the image. More precisely, γ is given by $1 - \mathrm{cdf}_s(l)$, where $\mathrm{cdf}_s(l)$ is the smoothed CDF for the value l. The smoothed CDF of the image is the normalized cumulative sum of the weighted PDF of the image, where the weighted PDF is obtained from the image PDF (histogram) by a power transformation with a exponent in the interval $(0, 1)$. The power transformation applied to the PDF aims to attenuate fluctuations in the smoothed CDF. In the actors results, it is observed a smaller degree of over enhancement.

J. Lee, Pant and H. Lee [3] combined CLAHE method with dynamic range compression [8] and used the local edge density to control the contrast gain. The strategy to control locally the contrast gain provides a significant improvement in comparison to standard CLAHE, avoiding over and under enhancement. The method was also able to boost detail information more than standard CLAHE for medical images.

Chang et al. [9] combined CLAHE with a dual gamma transformation in order to enhance both contrast and luminance. The authors proposed a heuristic to estimate the optimal CLAHE clipping point based on textureness and dynamic range information, thus avoiding under and over enhancement by CLAHE. The algorithm first redistribute the block histogram in CLAHE using the clip limit points. Then, it enlarges the luminance of image blocks by applying the first gamma correction. Finally, when the image block contains a large dynamic range, a second gamma correction is applied to compensate for dark regions and avoid over enhancement at bright regions. The results showed that the method, in comparison with CLAHE and others algorithms, is more apt to lit up dark regions while preserving naturalness. However, we can observe that some of the results have too little contrast. This can be due to the fact that their algorithm lits up all the dark tones, including those inside reasonably exposed segments, or due to small results for the clipping points provided by their heuristic (if this is the case, however, the clipping points can be increased by changing the parameters of their heuristic).

2.3 Alternative extensions for color images

As commented above, most histogram equalization based algorithms are extended to color images by acting on the luminance channel of a color system that separates all the luminance information into a single channel. This approach is not perfect. One of the problems is that it can generate unnatural colors, specially if there is a large variation on the luminance channel. For example, when the V component (value) from the HSV system is reduced for a region with a clear blue-white sky or for the figure of a person with very fair skin, the white-blue sky and the fair skin will become grayish. The reason for this is that, by changing $V = \max(R, G, B)$ for $V' < V$ while keeping the saturation $S = 1 - \min(R, G, B)/\max(R, G, B)$ constant, the chroma $C = \max(R, G, B) - \min(R, G, B)$ will be multiplied by the factor $V'/V < 1$, making the element look less colorful.

Another problem with simply transforming the luminance channel is that the color containing the new luminance can be nonexistent — i.e., the new color can be out of gamut. This will not happen for HSV and HSL color systems, because for them the space of valid combinations of parameters is a cube, but can happen for other popular systems such as LUV, HSI and L*a*b*.

In view of these limitations, several alternative methods were proposed to extend histogram equalization algorithms, or single channel image enhancement algorithms in general, to color images, as [10–16].

Recently, Ueda and Suetake [16] proposed the following interesting hue preserving transformation. Let x be the image to be corrected and R, G, B its RGB components, and consider $M = \max(R, G, B)$ and $m = \min(R, G, B)$, where max and min are computed for each pixel. Consider also $w = (1, 1, 1)$ and $k = (0, 0, 0)$. Let $[i]$ be the notation to specify the i-th pixel or element. It is straightforward to see that the i-th pixel of the image can be decomposed as

$$x[i] = a_w[i]w + a_k[i]k + a_c[i]c[i], \tag{1}$$

were $a_w[i] = m[i]$, $a_k[i] = 1 - M[i]$, $a_c[i] = M[i] - m[i]$ and

$$c[i] = \frac{x[i] - m[i]w}{M[i] - m[i]}. \tag{2}$$

Equation (1) is a representation of $x[i]$ as a convex combination of w, which is the pure white, k, which is the pure black, and $c[i]$, which is the purest (most colorful) color for the hue of $x[i]$. The combination is said to be convex because

$$a_w[i] + a_k[i] + a_c[i] = 1. \tag{3}$$

Furthermore, $a_w[i], a_k[i], a_c[i] \in [0, 1]$.

Fig. 1 – Comparing contrast enhancement by simple operation on a luminance channel with Ueda–Suetake method [16]. The first column contains the original images; the second column contains the images resulting from applying GHE to the V component in HSV system; the third column contains the images resulting from applying Ueda–Suetake method. The original images are from CEED2016 dataset [17] (available at `https://data.mendeley.com/datasets/3hfzp6vwkm/3`).

The method applies a histogram specification to the coefficient images a_w, a_k and a_c. The target histograms are the histograms that a_w, a_k and a_c would have if each possible RGB triplet was equally probable. Then, in order to preserve the relationship (3) after the histogram specification, the transformed a_w, a_k and a_c are divided by $a_w + a_k + a_c$ (element by element). The authors also proposed to control the amount of modification by linear combinations between the original and transformed values. The output image is given by (1), replacing a_w, a_k and a_c with their new values.

Figure 1 shows results of enhancing by applying GHE to the V channel in HSV system, and results of enhancing using the method proposed by Ueda and Suetake [16]. The HSV based approach produced an unnatural grayish effect, and also a somewhat dark result. The Ueda–Suetake method produced more vivid and natural results, and a more balanced brightness.

3. Learning based methods

Supervised machine learning techniques can be used to learn complex nonlinear transformations in image enhancement algorithms. In this class of methods, the models are usually trained using datasets with examples of non enhanced images and their enhanced counterparts [18]. Examples of supervised enhancement methods emerged in recent years are fully convolutional networks (FCN), reinforcement learning and U-Net [18].

Eilertsen et al. [19] designed a deep convolutional neural network (CNN) model to predict a high dynamic range (HDR) image corresponding to a low dynamic range (LDR) image. Their model is able to recover details missing due to the saturation of camera sensors. Convincing results for a wide range of images were achieved. While the objective of their method is to predict HDR images that can be viewed in HDR displays, when the HDR output is tone mapped into an LDR image to be used in regular LDR displays, the resulting LDR image can be seen as an enhanced version of the input image.

Yang et al. [20] proposed a method named Deep Reciprocating HDR Transformation (DRHT) to enhance images. The method uses a system with two fully convolutional encoder-decoder networks. The first network receives the LDR image to be enhanced and predicts an HDR image, recovering missing details due to camera saturation in this process (similarly as [19]). The second network executes a tone mapping of the HDR output of the first network. The two networks are integrated end-to-end for joint training and prediction. Experiments on standard benchmarks demonstrate that their method performs favorably against state-of-the-art image correction methods.

Liu et al. [21] also proposed a supervised system to reconstruct an HDR image from an LDR input. In contrast to previous learning based methods, their system uses domain knowledge of the LDR image formation process. More specifically, the authors modeled the HDR to LDR image formation process as (1) clipping, (2) nonlinear mapping from a camera response function and (3) quantization, and design three specialized CNNs to reverse these steps. They also jointly fine-tune the entire model end-to-end to reduce error accumulation. Their method obtained satisfactory results in comparison with other state-of-the-art single image HDR reconstruction algorithms.

Unsupervised learning techniques were also used for image enhancement. For example, Chen et al. [22] proposed an unpaired learning method for image enhancement based on the two-way generative adversarial networks (GANs) framework. Given a set of images with the desired characteristics, their method learns a photo enhancer which transforms an input image into an enhanced image with those characteristics.

4. Other methods

Yuan and Sun [23] proposed a method to correct exposure in images. The algorithm obtains S-shaped transformations adapted to the image needs. A zone-based region-level optimal exposure evaluation is derived for the algorithm. The authors also proposed a method to compensate for the compression of details in the middle tones produced when dark or bright ares are stretched. The results indicated that the proposed method enables better corrections than popular image editing tools and other automatic exposure correction methods.

Guo, Li and Ling [24] proposed a method based on retinex theory to correct low light images named low-light image enhancement (LIME). LIME estimates the illumination map by applying an edge preserving smoothing filter to the maximum of the R, G and B channels. The algorithm then applies a gamma transformation with $\gamma \in (0, 1)$ to the estimated illumination map, and divide the original image by the result. The algorithm may be interpreted as if it is multiplying the original image by a factor that is considerably larger than 1 for dark regions and slightly greater than or equal to 1 for adequately illuminated regions. The gamma transformation controls the degree of enhancement. LIME is strikingly effective at correcting low light images. Many other low light image enhancement algorithms emerged in the last years, but low light correction is not the focus of this review.

Zhang, Nie and Zheng [25] observed that LIME can also be used to correct over exposed images by simply inverting the input image (i.e., applying $f(x) = 1 - x$ to each channel), applying LIME to the inverted image and inverting back the result. The authors then proposed to apply (separately) both original and inverted LIME to a input image, and fuse the results with an algorithm that detects which result is more appropriate in each position. This way, they derived a method that corrects under and over exposure. Their method generates well balanced images with corrected exposure in many cases, but we can observe a slight tendency of the algorithm to produce a grayish or blackish effect, at least for the images and parameter choice used in the paper.

5. Conclusions and discussions

This paper reviewed algorithms for contrast enhancement and exposure correction, two important problems in many applications which are directly related. It was observed a large volume of methods, and that different approaches work better for different needs or objectives, and will demand different levels of computational resources.

In the class of histogram based methods, it was observed that many variants emerged as attempts to avoid distortions generated by previous method (e.g., methods that preserve the mean brightness). While these methods indeed avoid the distortions that motivated their proposals, they achieve this by trading some contrast enhancement capability. There are even extreme cases were the output image provided by the methods is almost equal to the input image. Therefore, these new methods must not be seen as replacements to the previous methods; instead, each method is specialized to tackle a class of problems or designed to specific applications.

Related to the question above is the use of certain quantitative performance metrics to evaluate and compare contrast enhancement or exposure correction algorithms. Some of the most popular performance metrics are Absolute Mean Brightness Error (AMBE), Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Lightness Order Error (LOE). These metrics attempt to measure the degree of distortion between two images, with respect to some attribute. In the literature of image enhancement, normally they are used to measure the distortion between the original and the processed image, and frequently it is understood in the researches and surveys that the more distortion these metrics indicate, the worse must be considered the performance. However, if the output image is almost equal to the input image, then these metrics will measure almost no distortion, and thus both high and low values may indicate unsatisfactory performance. The better is not to rely solely on these metrics and use also subjective user evaluation, when suitable, and other performance metrics not based on the distortion between input and output. A solution by Guo, Li and Ling [24] was to use LOE to measure the distortion not between the original and enhanced images, but between the enhanced and the ground truth images (which the dataset used by them contained).

It was also observed a growing use of learning based methods in this field, specially methods using CNNs. This can be related to the growth of computational power and resources in the last years. Such heavy learning based methods have accomplished impressive tasks, but they also have some drawbacks. First, the models used (often CNNs) are huge neural networks with a large number of layers, which makes these methods computationally intensive. Second, these methods will likely perform badly if the input images are very different from the images used in the training dataset. Third, the behavior of these models is unpredictable, specially for images very different from the images used in the training dataset. Fourth, the convolutions generate halos that are sometimes clearly visible in the outputs of the models. As a consequence, analytical or exact approaches will continue to be used, and newer methods in such category will continue to be developed in the foreseeable future.

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