Follow this and additional works at: https://www.tdcommons.org/dpubs_series

Recommended Citation
N/A, "Face Image Normalization For Authentication Under Diverse Lighting Conditions", Technical Disclosure Commons, (July 09, 2020)
https://www.tdcommons.org/dpubs_series/3414

This work is licensed under a Creative Commons Attribution 4.0 License.
This Article is brought to you for free and open access by Technical Disclosure Commons. It has been accepted for inclusion in Defensive Publications Series by an authorized administrator of Technical Disclosure Commons.
Face Image Normalization For Authentication Under Diverse Lighting Conditions

ABSTRACT

Authentication based on face recognition can fail under poor lighting or exposure conditions. This disclosure describes techniques to improve the brightness and/or contrast of a given facial image such that face recognition based authentication can be performed robustly over a wide range of lighting or exposure conditions. Brightness is improved using gamma correction, where the optimal gamma value is given by a low-complexity, closed-form formula. Contrast is improved by subjecting pixel intensities to a mapping that results in better color saturation, or a larger standard deviation of pixel intensities. The techniques work on near infra-red (NIR) as well as visible-spectrum (RGB) images.

KEYWORDS

- Face recognition
- Face authentication
- User authentication
- Image normalization
- Brightness normalization
- Gamma correction
- Contrast normalization
- Near infra-red (NIR)
- Luminance
- Chrominence
BACKGROUND

Fig. 1: Illustration showing Images obtained under conditions of poor lighting or exposure: (a) and (b) are images taken indoors, while (c) and (d) are taken outdoors

Authentication based on face recognition can fail under poor lighting or exposure conditions. For example, Fig. 1(a)-(b) illustrates (mockup) images of faces that are captured indoors using the near infra-red (NIR) part of the spectrum. The figures show insufficient lighting (Fig. 1(a)), or excess exposure (Fig. 1(b)). Fig. 1(c)-(d) illustrate similar problems for images taken outdoors. Similar issues exist with images taken with the visible (referred to as RGB) parts of the spectrum, and also with fingerprint-based authenticators. In general, image
quality varies significantly with the capturing environment, the sensors, the light emitter (flash) strength, the distance to the device, the auto-exposure / auto-gain algorithms of the camera, etc.

The lack of brightness and contrast in facial images presented for authentication is further confirmed by histograms of pixel intensities obtained under various conditions of shutter-speed and flash intensity, as illustrated in Fig. 2. Not only are the mean values well below the midpoint (128) of the dynamic range (0-255), the histograms are rather narrow in width, indicating insufficient contrast.

Poor authentication performance on facial images such as those displayed in Fig. 1 can be traced to the lack of brightness and/or contrast in the images. One technique of improving brightness is based on gamma correction. Under gamma correction, the intensity $I_{in}$ of a pixel is non-linearly mapped to an intensity $I_{out}$ using the formula

![Histograms of pixel intensities obtained over a large corpus of images using NIR light, at various exposure conditions](image)

**Fig. 2: Histograms of pixel intensities obtained over a large corpus of images using NIR light, at various exposure conditions**
\[ I_{out} = 255 \times \left( \frac{I_{in}}{255} \right)^\gamma. \]

**Fig. 3: Gamma correction**

Fig. 3 illustrates a plot of output versus input pixel intensity with \( \gamma \) as a parameter. Brightness can be improved by iteratively increasing or decreasing gamma until the average pixel value over the region of a user’s face is at a threshold set, e.g., to one-half the dynamic range of pixel intensity.

**Fig. 4: An iterative method to increase mean pixel-brightness by adjusting \( \gamma \)**
This is illustrated in Fig. 4, where an appropriate value for γ is obtained iteratively as the value that increases the mean pixel brightness just above a threshold, set to 128. The improvement in clarity of the output image over the input image is evident.

Although the iterative technique to improve brightness does result in improved clarity, determining an optimal γ value is a relatively complex procedure, involving the repeated computation of mean pixel value. Besides, gamma correction by itself does not improve contrast.

DESCRIPTION

This disclosure describes a closed-form solution to determine the optimal γ to effect brightness improvement (or normalization) by gamma correction. The disclosure also describes a mapping that transforms pixel intensities to improve contrast; this is referred to as contrast normalization.

Brightness normalization

Per the techniques, an optimal γ used for gamma correcting an image is given by

\[ \gamma^* = \log \left( \frac{\mu_{\text{REF}}}{255} \right) / \log \left( \frac{\mu_{\text{FACE}}}{255} \right), \]

where

- \( \gamma^* \) is the value of the optimal γ;
- \( \mu_{\text{REF}} \) is a target mean value for the pixels in the face-segment of an image, typically set to 128, the midpoint of the pixel dynamic range (0-255); and
- \( \mu_{\text{FACE}} \) is the present value of the mean of the pixels in the face-segment of the image.

In contrast to iterative gamma correction, the disclosed techniques require just one computation of the mean value of the pixels in the face-segment of the image. The brightness and clarity
improvement wrought by gamma correction using the disclosed, closed-form, optimal gamma is substantially similar to the improvement obtained by iterative gamma correction.

**Contrast normalization**

Per the techniques, the intensity of a pixel $X_{ijk}$ located at the $i$th row, the $j$th column, and on the $k$th channel (a channel being, e.g., a red, blue, green, or grayscale channel) is transformed to an intensity $X'_{ijk}$ to reach a target standard deviation $s$, using the following formula.

$$X'_{ijk} = s \frac{X_{ijk} - \mu_{FACE}}{\max\{\epsilon, \sqrt{\lambda + \frac{1}{nrc} \sum_{i=1}^{r} \sum_{j=1}^{c} \sum_{k=1}^{n} (X_{ijk} - \mu_{FACE})^2}\}}$$

In this formula,

- $\mu_{FACE}$ is the mean value of the pixels in the face-segment of the image, same as the mean value used in brightness normalization;
- $\epsilon$ is a small number used to avoid divide-by-zero conditions;
- $\lambda$ is a positive regularization term to bias the standard deviation;
- $r$ is the number of rows in the image;
- $c$ is the number of rows in the image; and
- $n$ is the number of channels in the image, e.g., $n = 3$ for a visible-spectrum RGB image, $n = 1$ for an NIR image, etc.
Fig. 5: (a) Original images; (b) images after brightness normalization; (c) images after brightness and contrast normalization.

Fig. 5 illustrates examples of (mockup) images whose clarity has been improved using the brightness and contrast normalization techniques described herein. Fig. 5(a) illustrates original images, taken with NIR light under poor exposure conditions. Fig. 5(b) illustrates the images after brightness normalization. Fig. 5(c) illustrates the images after brightness and contrast normalization. The improved clarity evident from Fig. 5(c) enables face-based authentication and other face-recognition applications to perform more robustly.
As illustrated in Fig. 6, the improved clarity is reflected in the histograms of the pixel intensities of the images. Fig. 6(a), which illustrates the histograms of original images taken under poor exposure conditions, presents a mean pixel-value well below one-half of the pixel.
dynamic range. The histograms are also considerably compressed, indicating insufficient contrast. Fig. 6(b), which illustrates histograms after brightness normalization, shows an improvement in mean value, e.g., mean values closer to one-half of the pixel dynamic range. Fig. 6(c), which illustrates histograms after brightness and contrast normalization, shows not only an improved mean value but also a greater dynamic range (larger standard deviation), corresponding to good contrast.

**Brightness and contrast normalization for visible-spectrum (RGB) images**

![Diagram](image)

**Fig. 7: Brightness and contrast normalization for RGB images**

For images taken in the visible part of the spectrum, e.g., those with red, blue, and green channels, brightness and contrast normalization (BCN) can be executed as illustrated in Fig. 7. The RGB image is converted to YUV (luminance-chrominance) format (702). BCN is applied on the Y-channel alone (704), using Formulas (1) and (2) described above. The transformed YUV image is converted back to RGB format (706). Per the techniques, the Y channel, which captures the luminance, is manipulated using single-channel BCN, enabling adjustment of the description of the intensity of light. Since color information is separated into the U and V channels, the original color is largely retained while the image clarity is improved via the BCN procedure.
Fig. 8: Brightness and contrast normalization of RGB images. The columns correspond to various exposure levels (shutter speeds). (a) Original RGB images; (b) YUV images; (c) After BCN operation on the Y channel; (d) Re-transformation to RGB format after BCN on the Y-channel.
Fig. 8 illustrates brightness and contrast normalization of (mockup) RGB images, per the techniques of this disclosure. The columns correspond to various exposure levels (shutter speeds). Fig. 8(a) are the original images; at low exposures, they are seen to be quite unintelligible. Fig. 8(b) are the images after conversion to YUV format. Fig. 8(c) are the images after BCN operation on the Y channel. Fig. 8(d) are the images after transformation back to RGB format, following the BCN operation on the Y channel.

The improved clarity evident from Fig. 8(d) enables face-based authentication and other face-recognition applications to perform more robustly. The techniques perform similarly well at a variety of apertures, ISOs, camera-subject distances, etc. The techniques are applicable for images that are captured indoors as well as outdoors. In particular, in outdoor photography, they reduce substantially both glare and facial shadows, such that face-recognition based authentication services perform more robustly.
As illustrated in Fig. 9, the improved clarity is reflected in the histograms of the pixel intensities of the images. Fig. 9(a), which illustrates the histograms of original images, presents a mean pixel-value (for most exposures) well below one-half of the pixel dynamic range. The histograms are also considerably compressed, indicating insufficient contrast. Fig. 9(b), which illustrates histograms after RGB→YUV transformation, shows a similar low-mean, compressed characteristic. Fig. 9(c), which illustrates histograms after BCN on the Y-channel, shows not only an improved mean value but also a greater dynamic range (larger standard deviation), e.g., good contrast. Fig. 9(d), which illustrates histograms after YUV→RGB transformation following BCN on the Y-channel, also shows an improved mean value and good contrast.

In this manner, the techniques of this disclosure use statistics of the object region of the image, e.g., face, fingerprint, etc., to normalize the brightness and clarity of the entire image. The disclosed techniques improve image clarity in various applications, e.g., authentication, recreational photography, CCTV-based security, etc. The ability to explicitly set target image...
statistics, e.g., mean and standard deviation, of the image facilitates the normalization process for regular convolutional neural network (CNN) training, due to the zero-mean property of the learned kernels. In addition, explicit settings also benefit model quantization, because the quantized input to the CNN requires an input mean and standard deviation.

CONCLUSION

This disclosure describes techniques to improve the brightness and/or contrast of a given facial image such that face-recognition based authentication services perform robustly over a wide range of lighting or exposure conditions. Brightness is improved using gamma correction, where the optimal gamma value is given by a low-complexity, closed-form formula. Contrast is improved by subjecting pixel intensities to a mapping that results in better color saturation, or a larger standard deviation of pixel intensities. The techniques work on near infra-red (NIR) as well as visible-spectrum (RGB) images.

REFERENCES