The Effect of Pre-Processing Algorithms on Facial Expression Recognition Focusing on Illumination Variance in Poorly Lit Images

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Abstract

Facial Expression Recognition (FER) can be applied to various research areas, and with the emergence of modern technologies, FER systems have increased accuracy in real-world applications, instead of just laboratory environments. Although there has been an increase in accuracy, there is still a wide gap between laboratory-controlled systems, which average approximately 97% accuracy, and the application of these systems to real-world scenarios, which average approximately 50% accuracy. One of the main issues that cause this difference in accuracy is illumination variation. This research investigates methods for increasing accuracy of FER systems for experiential and real-world scenarios, by investigating the effect of select enhancement pre-processing filters on poorly lit images, or images with illumination variation before passing an image to a FER system, such as Google Cloud Vision, or detection. The pre-processing algorithms selected were histogram equalization, contrast limited adaptive histogram equalization, and denoising. A proposed hybrid method of combining these algorithms was also applied. From our experimentation using the YALE faces dataset, the results obtained showed that the proposed method increased accuracy for facial images with lower illumination poorly lit images by as much as 15%. However, when applied to facial images with higher illumination and well lit, there is an overall decrease in accuracy.

Keywords: facial expression recognition, image denoising, OpenCV, Google's Vision API

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Introduction

FER systems are incredibly complex systems, whose accuracy can be easily influenced by noise or artefacts in the input images (Ekundayo & Viriri, 2022). Variations in illumination and changes in the subject's head pose can impact the accuracy of facial expression recognition systems. Extracting facial landmarks is a key stage in FER systems, and the performance of feature extractions is impacted heavily by the challenges above. FER systems are more robust in performance when the variations of the extracted features are lessened, and when the intra-class and the inter-class variations are maximized; thus, good feature representation can improve efficiency and accuracy in the recognition process (Bah & Xue, 2022). Preprocessing of the input image is a necessary step to reduce the challenges that can be caused by occlusion and variation in illumination and head position. Preprocessing can positively impact the robustness of the feature extraction stage and, thus, improve the overall performance of FER systems. Some features involved in the preprocessing stage include emotion features, geometric features, and pixel intensity.

This research investigation is focused on the effects of illumination variation and its impact on facial expression recognition. Different angles of a light source, or multiple light sources, can affect the appearance of facial features and characteristics. Performance of the recognition techniques has achieved noteworthy results under controlled environments, where illumination is monitored, controlled, and taken into consideration when obtaining source data to pass through FER systems (Ekundayo & Viriri, 2022).

Several methods have been developed to solve illumination variation problems. Deep learning has been developed with a higher accuracy and more complex structure, but common deep learning techniques require large databases, more computation time for training, and high-power consumption (Canedo & Neeves et al., 2022). Other methods such as the "Illumination Cones" method (Salamh & Akyüz,2022) and "9 D linear Subspace" (Basri & Jacobs, 2003) were also used; however, these methods require a large amount of data and positional knowledge such as the coordinates for the light source to function properly (Turan et al., 2020).

Due to these limitations, this research focuses on running preprocessing algorithms on input images to FER systems, with the aim to limit the effect of illumination variation on the accuracy of these systems. The preprocessing algorithms discussed in this research would require significantly less processing power, or processing time, to produce an altered output image, without the need for extra positional data about the illumination sources, thus making them more suitable for real world applications.

Background

Pre-processing algorithms are methods used to prepare images for further analysis which include, but are not limited to, image filtering, enhancement, restoration, feature extraction, object recognition, segmentation, and classification. Image pre-processing is often a necessary step to remove noise and other unwanted image artefacts before further processing of the image. Optimal use of image pre-processing methods can provide benefits towards solving problems that ultimately lead to better local and global feature detection (Krig, 2014). There are many image pre-processing methods that exist in the literature; however, these methods are often categorised based on the domain in which they operate such as the spatial domain, spectral domain, and frequency domain. Image pre-processing techniques have a range of applications in entertainment, social science, and engineering with several real-world applications (Deshmukh & Vibhute, 2020). Many spatial preprocessing techniques such as histogram equalization, denoising, image segmentation and image filtering methods have been used in real-world applications due to the speed at runtime which can provide faster image processing in real-time (Christo et. al., 2022). Digital image pre-processing techniques have been applied successfully in the food industry to identify defects in food products, as well as identifying the likelihood of fungi, insect and disease infestations on fruits, vegetables, and other food products (Chithra & Bhavani, 2019). Digital image preprocessing techniques have been applied successfully in the medical field in a range of applications including tumor detection, organ segmentation, and foetus and tissue deformation derived from x-ray and Magnetic Resonance Imaging (MRI) sequences (Patel & Bhosale, 2022).

Digital image pre-processing techniques have been successfully applied to automotive industry in a range of applications including license plate recognition, vehicle model identification, and in driverless vehicle operations such as lane recognition, traffic lights and road sign detection (Chen et. al., 2020; Parekh et. al., 2022). Digital image processing techniques have also been applied successfully to improving visual perceptions of humans in a wide range of scenarios including biometric recognition of fingerprints using regular expression machines, facial recognition, iris recognition and gait recognition (Phillips et. al., 2018). In this research investigation, select spatial digital image pre-processing methods are investigated to explore their effects on FER systems such as Google's Cloud Vision Application Programming Interface (API).

Histogram Equalization

Histogram Equalization distributes pixels between a floor and a ceiling through a contrast remapping function to spread out the range of intensities more evenly (Krig, 2014). This process generally leads to an increase in the global contrast of many images by brightening the darker areas of the image. This method works well for greyscale images, whereas colour images should be equalized in a specified colour space for optimal results. Gonzalez and Woods (2018) outline the Histogram Equalization algorithm below:

Let f be a given image represented as a m_r by m_c matrix of integer pixel intensities ranging from 0 to L − 1. L is the number of possible intensity values, often 256. Let p denote the normalized histogram of f with a bin for each possible intensity. So

$$p_n = \frac{number\ of\ pixels\ with\ intensity\ n}{total\ number\ of\ pixels} \quad n = 0, 1, \ldots, L-1$$

The histogram equalized image g will be defined by

$$g_{i,j} = floor((L-1)\sum_{n=0}^{f_{i,j}} p_n), \tag{1}$$

where $floor$ rounds down to the nearest integer. This is equivalent to transforming the pixel intensities, k, of f by the function

$$T(k) = floor\ ((L-1)\sum_{n=0}^{k} p_n)\,.$$

The motivation for this transformation comes from thinking of the intensities of f and g as continuous random variables X, Y on [0, L − 1] with Y defined by

$$Y = T(X) = (L-1)\int_0^X p_X(x)dx, \tag{2}$$

where p_X is the probability density function of f. T is the cumulative distributive function of X multiplied by (L − 1). Assume for simplicity that T is differentiable and invertible. It can then be shown that Y defined by $T(X)$ is uniformly distributed on *[0, L − 1]*, namely that $p_Y(y) = 1/(L-1)$.

$$\int_0^y p_Y(z)dz = probability\ that\ 0 \le Y \le y$$

$$= probability\ that\ 0\ \le X \le T^{-1}(y)$$

$$= \int_0^{T^{-1}(y)} p_X(w)dw$$

$$\frac{d}{dy}\left(\int_0^y p_Y(z)dz\right) = \ p_Y(y) = \ p_X\big(T^{-1}(y)\big)\frac{d}{dy}\big(T^{-1}(y)\big).$$

Note that

$$\frac{d}{dy}T\big(T^{-1}(y)\big) = \ \frac{d}{dy}y = 1$$

So,

$$\frac{dT}{dx}|_{x=T^{-1}(y)}\frac{d}{dy}\big(T^{-1}(y)\big) = (L-1)p_X\big(T^{-1}(y)\big)\frac{d}{dy}\big(T^{-1}(y)\big) = 1$$

Which means the histogram equalized image can provide a good approximation of the cumulative frequency distributions of the pixel intensities in the original image and thus, enhance the contrast in the processed image.

$$p_Y(y) = \ \frac{1}{L-1}$$

Contrast Limited Adaptive Histogram Equalization (CLAHE)

Histogram equalization can result in the oversaturation of some images depending on the contrast levels of the background and foreground, and often introduces artefacts or noise into the image. To solve this problem, adaptive histogram equalization is used by dividing the image into small blocks called “tiles.” This effectively amplifies noise if it is present in near-constant regions.

Contrast limiting is introduced to limit the histogram bin by a specified contrast limit and thus, reduces the problem of noise amplification.

Non-Local Means Denoising

Buades et al. (2011) described a method for denoising an image based on the principle of replacing the color of a pixel with an average of the colours of similar pixels such that each is restored as an average of the most similar pixels within a specified region. Therefore, a vast portion of the image must be searched to locate all the pixels that resemble the pixel one wants to denoise. The size of the region impacts the amount of noise reduced and the resemblance is evaluated using a non-local means filter and is written:

$NLu(p) = \frac{1}{C(p)} \int f(d\big(B(p), B(q)\big)u(q)dq,$e

Where

D(B(p), B(q)) is a Euclidean distance between image patches centered respectively at *p* and *q*, *f* is a decreasing function and *C(p)* is the normalizing factor.

Related Works

Chen and Cheng (2015) propose a design for a facial expression recognition system based on the edge detection algorithm, first for image preprocessing to locate the eyes and lips of the face and to extract the shape of the face to build a database of facial expressions. Their research demonstrated how the positioning of the eyes and lips can be obtained via different edge detection operators such as Canny, Laplace, Sobel, and Robert; and determine that the Canny operator was the best choice for recognition accuracy. The design used did not factor in the effect of noise or the effects of illumination on the input image. Our study follows the same approach used by Chen and Chen (2015) but seeks to explore the effects that varying standardized illumination levels would have on the selected dataset.

Calvo et al. (2013) investigated the influence of the pre-processing stage on the classification performance of a face recognition analysis. The study showed how different preprocessing algorithms interact with each other and the degree to which they affect the overall Facial Recognition System. The dataset used for these tests was made sure to have been as close to a real-world environment as possible so that the difficulties associated with such an implementation could be addressed. Other research studies by Chen and Cheng did not address issues of illumination which is a critical component for real world application.

Methodology

This research utilised the Yale facial database for experimentation as it contained varying illumination on facial features and captured images of subjects in varying lighting conditions. The research approach focused on images that were poorly lit to investigate the problem of illumination on facial expression recognition. The Yale face database consists of 165 images (grayscale) taken from 15 people under diverse facial expressions and light conditions. The dataset included 11 images for every individual, with various facial expressions or environmental conditions, such as, normal, wearing glasses and no glasses, center-light, left and right light, happy, winking, sleepy, surprised and sad. Most importantly for this research, the dataset included images with controlled light intensities but varied standardized illumination positions, such as a left light source, center light source (included to show performance with a standard image with average illumination) and a right light source as shown in Figure 1 below:

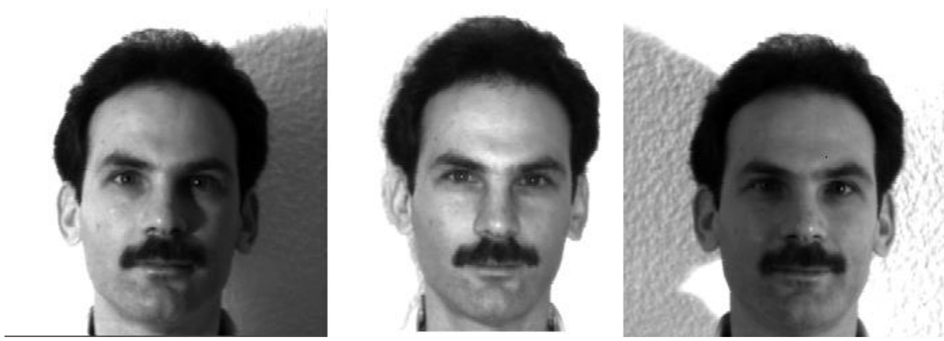

Figure 1: Illumination differences in select image "subject02"

The methodology focused on applying the discussed pre-processing algorithms on the images with lighting variations and evaluating the accuracy on the input versus output from the google vision library.

Image manipulation was performed in python with the use of the 'OpenCV' library to load image files as arrays, which can then be operated on using the various mathematical functions found in the default math library, or within the 'OpenCV' library itself. Images were passed into the python using OpenCV's 'imgread' function, after which an output image was generated after manipulation using one of the chosen algorithms from the background section. A final output image was also produced after running all the chosen algorithms on the input image in the following sequence: histogram equalization -> contrast limited histogram equalization -> denoising (non-local means). Thus, a hybrid approach was used by combining all selected algorithms.

The results of the image manipulation processes were compared using Google's Vision API, which uses a pre-trained model to detect the likelihood of five emotions in images with faces. The percentage confidence in the emotion output via the Vision API will be used as the measure of accuracy when comparing the input image (non-manipulated) versus the output images (image manipulated by each algorithm, and the sequence of algorithms). An example of the Vision API output with a non-manipulated image is shown below:

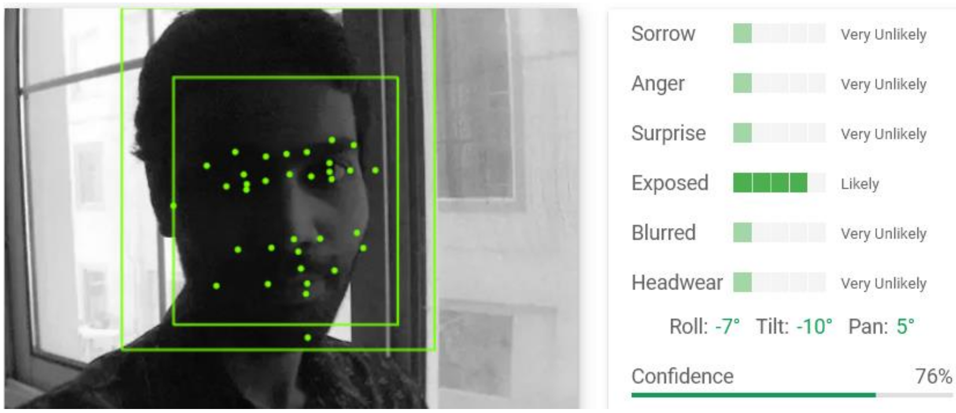

Figure 2: Google's Vision API output

As shown in Figure 2, the facial expression detected is "exposed" at 76% confidence, indicating the amount of illumination present in the image, while the source described the subject as having a "neutral" facial expression. This difference in expression recognition is caused by the lack of detail in the left half of the facial image, which is obscured by shadow due to most of the light being emitted from the right of the facial image of the subject. Image manipulations discussed in this paper aimed to preserve the data in the left half of the facial image and, thereby, increase the accuracy of the result obtained from the API.

Experiment Analysis and Performance

In order to evaluate the performance of the selected algorithms and the proposed method on the Yale Facial dataset, the 'confidence' metric provided by Google's Vision API was used. The selected algorithms, as well as the proposed method, were executed using "left light source", "right light source" and "centre light source" images as an input from the dataset, after which, output and input images were passed into the Vision API and the "confidence" metric was recorded for both input and output images. A breakdown of the experimentation approach is shown below, in figure 3, as applied to a sample image whose subject is not lit properly, and a source expression of "neutral" is defined.

It should be noted that before the images were processed, some pre-processing was done. The images in the Yale Faces Dataset were all without a file extension but were of the filetype "GIF". As the OpenCV library did not support "GIF" images, a PowerShell script was created that added the "GIF" file extension, and a conversion to the file type "JPG" was performed. These input images were processed as grayscale and then passed on to Python for manipulation to mitigate any loss of image quality.

The input image (Figure 3) is passed into the Vision API after which the reference confidence metric image was recorded. Figure 6 shows the output image after the image was denoised, which does not restore any data in the dark areas of the face, but instead removes any artefacts found in the image.

Figure 3: Original Input Image

Histogram Equalization was then applied to the image. Figures 4 and 5 show the input and output image histograms and computed cumulative frequency distributions respectively. As shown in the input histogram, much of the image's data is contained in the darker pixel intensities. After equalization, we can see that the output histogram restores some of the intensities of the image, thereby restoring some of the data on the left side of the subject's facial image as shown in the output image, figure 6. The output demonstrated that histogram equalization introduced artefacts or noise in the image.

Figure 6 shows the output after the CLAHE algorithm was applied to the input image. Through previous experimentation, it was determined that a tile size of 20x20 pixels and a contrast threshold or limit of 2 reduce the artefacts generated from histogram equalization. However, it was observed that more data is restored in the poorly lit areas in the image from the histogram equalization algorithm.

Lastly, figure 6 shows the effect of the proposed method on the input image, with a combination of all algorithms in the order specified. Denoising is done last to reduce the artefacts generated from effectively performing histogram equalization; however, it can be clearly seen that some of the artefacts remained in the image.

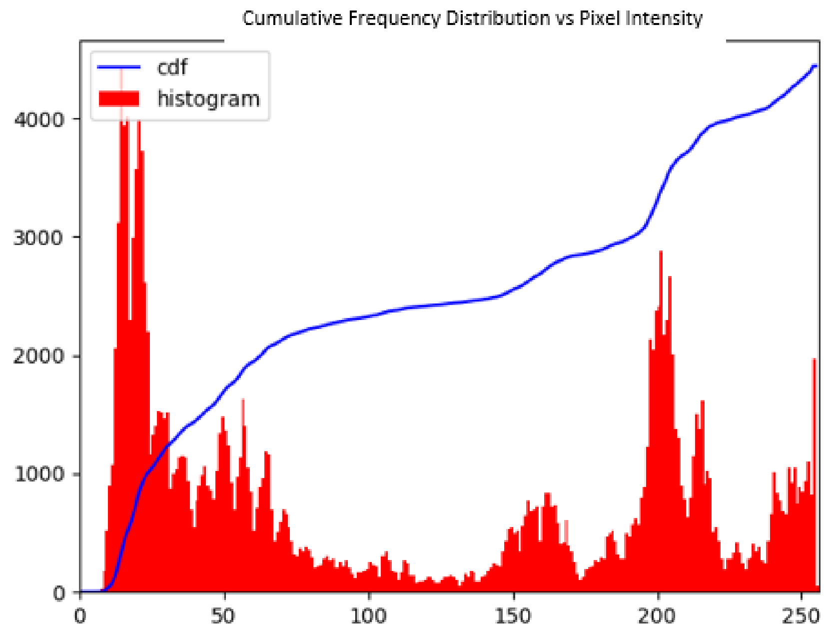

Figure 4: Input Histogram

Cumulative Frequency Distribution (y-axis) vs Pixel Intensities (x-axis)

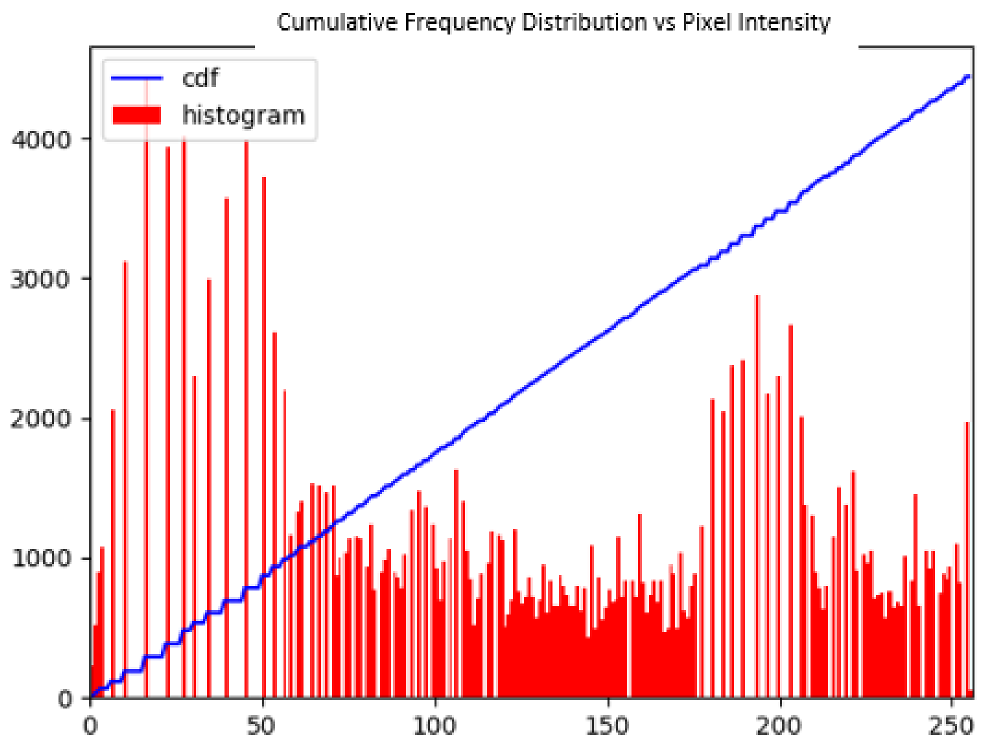

Figure 5: Output Histogram

Cumulative Frequency Distribution (y-axis) vs Pixel Intensity (x-axis)

Joshua Boodhu, Micah Pooran & Laurice Phillips

Figure 6: Output from Google Vision API (L->R Original, Denoised, HEQ, CLAHE)

The results obtained from Vision AI are shown above for each respective algorithm. As shown for this sample image, the expression detected from the input and denoised image was "exposed" which does not match the "neutral" expression as provided. However, after the application of histogram equalization, CLAHE and the proposed method, it is observed that a neutral expression is obtained, with the proposed method achieving the highest confidence for the sample image, as shown by the output image and result below. Although many facial expressions exist, in the context of this research, the reduced likelihood of the other facial expressions with increased confidence of the processed sample matches empirical observation of a more neutral facial expression as shown in the figure 6.

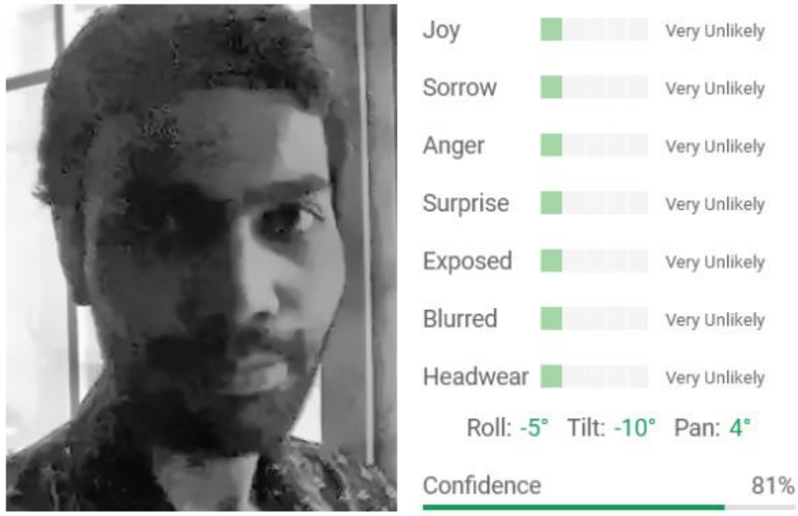

Figure 7: Output from Google Vision API (Proposed Method)

As shown above in Figure 7, a confidence percentage value is obtained from Google's FER system. For each image manipulated by the selected algorithms, this confidence percentage was extracted and tabulated, to be compared against the confidence result from the original image. Figures 8, 9 and 11 illustrate generated graph results which better outlined the differences in accuracies, as discussed in the research analysis. These graphs were separated based on the differences in lighting: Left Illuminated, Right Illuminated and Center Illuminated (which represents a standard well-lit image).

Results Analysis and Discussion

From the research methodology and experimentation approach, results were extracted and illustrated in the graphs below. Figure 8 shows that the method proposed reduced the accuracy of the FER system by approximately 15%. Based on the image manipulation methods chosen, this was expected, as the images whose subjects were lit from the centre had most of their faces well lit. This means that most pixels will be of a brighter intensity, thus Histogram Equalization and CLAHE combined would overexpose the bright areas, thereby reducing the visibility of key facial landmarks. Denoising performed closely to the unmanipulated image as the blurring effect of denoising did not seem to affect Google's FER system to a considerable extent. Further research is needed to identify suitable image processing algorithms and techniques to effectively mitigate against overexposure of facial expression images in global or partial image regions due to illumination sources.

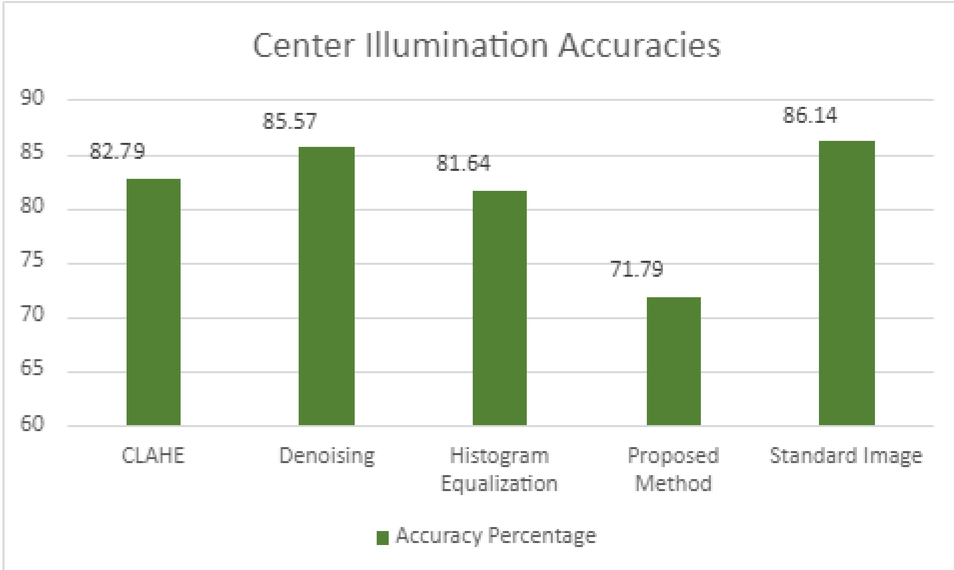

Figure 8: Centre Illumination

Percentage Accuracy (y-axis) vs Image Enhancement Method (x-axis)

From the results shown in figure 9, we observed that denoising the image increased the accuracy of FER by 0.53%. The proposed method decreased the accuracy by 7%. In the set of images from the chosen dataset that are illuminated from the right, the proposed method increased the accuracy on "subject 07" as shown below by 5%.

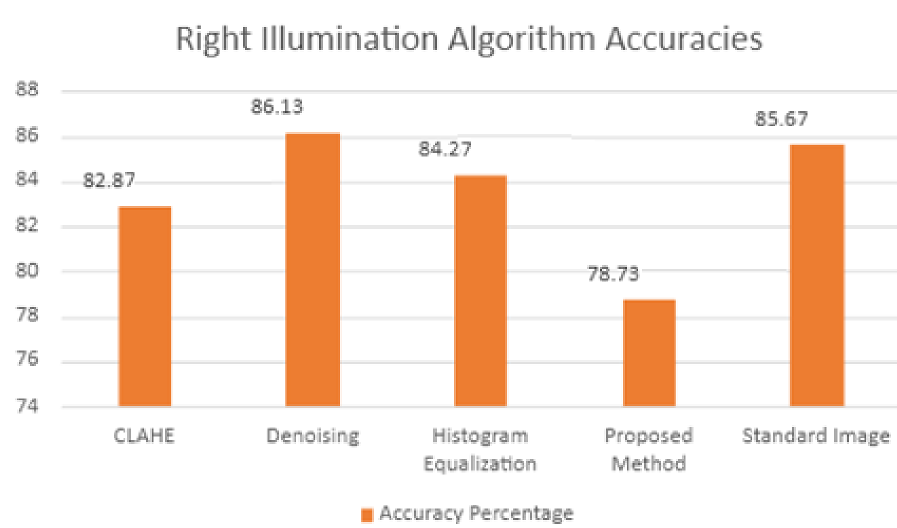

Figure 9: Right Illumination

Percentage Accuracy (y-axis) vs Image Enhancement Method (x-axis)

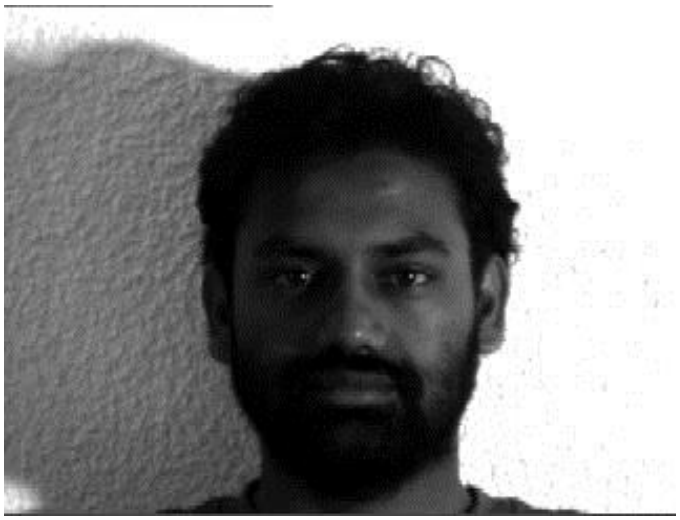

Figure 10: Image of "subject 07"

From Figure 10, a darker skin tone of the subject is observed, and the left side of the facial image is lit more poorly than found in other images from the dataset. This positive result from the proposed method was also repeated among other subjects that had a darker skin tone, and a more poorly lit face.

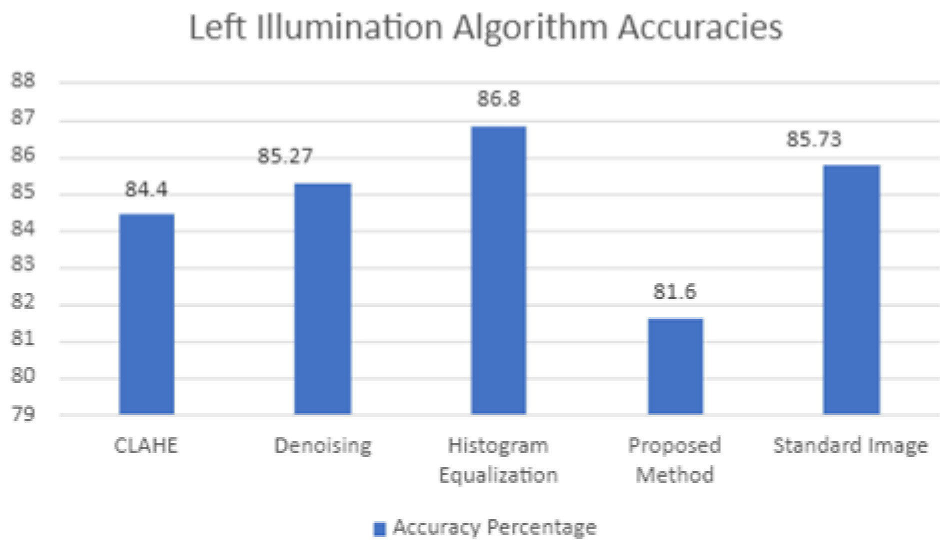

Figure 11: Left Illumination

Percentage Accuracy (y-axis) vs Image Enhancement Method (x-axis)

From the results above, it is observed that denoising did not increase the accuracy of FER significantly. The proposed method decreased accuracy by approximately 4%. From the input images, the proposed method was observed to perform best on subjects with a darker skin tone, and whose photograph were more poorly lit. For example, from the chosen dataset, the proposed method increased the accuracy of the FER system by 5% on “subject 13” as shown below:

Figure 12: Image of "subject 13"

From figure 12 above, it was observed that the right side of the facial image is very poorly lit. The improved accuracy and positive result were repeatedly observed with other facial images of similar lower illumination levels from the dataset. In facial images of higher illumination, it was observed that the average accuracy of the proposed method was decreased overall when compared to the standard, non-manipulated image.

Conclusion

In conclusion, the proposed method showed improved accuracy for lower illuminated facial images; but for facial images with higher illumination, the proposed method was not as effective as the other preprocessing algorithms listed. This conclusion was derived through experimentation and comparative analysis of the effect of preprocessing algorithms on the YALE dataset of images with varying illumination levels. For future research works, a dataset consisting of more dimly lit images as well as persons with more varied skin tones can be used, along with the testing of other image manipulation techniques for dimly lit images, such as gamma correction. These results provide new insight into the role of preprocessing algorithms in dealing with poor lighting situations and are, thus, useful in the design of new methods for robust facial expression recognition in experiential and real-world applications. In future research, experimentation using additional pre-processing algorithms will be performed on a variety of appropriate datasets that include a higher number of images with more varied and controlled illumination aspects. The goal is to derive more optimal pre-processing algorithms and approaches to improve facial expression recognition systems by performing select enhancement strategies, particularly on poorer quality facial images. The future research work can also investigate select off-the-shelf image enhancing software in comparison to proposed methods.

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