Evaluation of contrast enhancement methods on finger vein NIR images

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Abstract. Biometrics is a technology used to identify a person based on physical characteristics and behavioural characteristics. Biometrics is used to increase the importance of personal data. However, many biometric models can be manipulated, such as fingerprints. To cover the fragility, a biometric pattern based on a blood vein, such as a finger vein pattern, was developed. To obtain a clear image of the finger vein, one of the acquisition tools is called Near-Infrared (NIR). Despite using NIR technology in the acquisition process, it is not uncommon for the finger vein pattern to be unclear. To overcome this problem, it is necessary to increase the contrast quality of the image. This study proposes the use of the BPDFHE method to improve the contrast quality of finger vein NIR images. As a comparison material for performance tests, the HE, AHE, and CLAHE methods were also tested. The test is carried out according to AMBE, PSNR, SSIM, FSIM, and computation time parameters. Based on the test, the results showed that the BPDFHE obtains AMBE, PSNR, SSIM, and FSIM up to 0.054, 26.873, 0.840, and 0.906, respectively. It also gains less computation time up to 10.988 seconds. These results indicate that BPDFHE is an effective and efficient method in improving the contrast quality of finger vein NIR images.

1. Introduction

Biometrics is a technology used for identifying a person based on physical characteristics and behavioral characteristics. Biometrics is used to increase the importance of personal data. However, many biometric models can be manipulated, such as fingerprints. Fingerprints were an authentic trait that each person owns, but can be loot by using advanced methods. Thus, allowing that person to gain authority that they should not have access. Besides, fingerprints are also prone to changing patterns due to frequent contact with objects.

To cover the fragility, a biometric pattern based on a blood vein was developed. One of which is the finger vein pattern[1–3]. Biometrics with finger veins are used because of the advantage of being resistant to external interference, so it does not easily change. However, because it lies just below the surface of the skin, it can be a challenge to obtain a clear finger vein image pattern. To obtain a clear image of the finger vein, the acquisition used a tool called Near-Infrared (NIR). NIR technology was utilized because it has a short wavelength, i.e. 0.75 – 1.4 μm. The illustration of the finger vein-based authentication process as depicted in Figure 1.

Despite using NIR technology in the acquisition process, it is not uncommon for the finger vein pattern to be unclear. This is due to various factors, such as skin thickness, ambient light, condition of
the acquisition tool. Figure 2 is illustrating the various contrast condition on the finger vein NIR image. To overcome this problem, it is necessary to increase the contrast quality of the image. Contrast quality enhancement often implements fairly familiar methods such as histogram equalization (HE), adaptive histogram equalization (AHE), and contrast limited adaptive histogram equalization (CLAHE). Each of these methods, of course, has its advantages and disadvantages. HE is the basic method for improving image contrast quality by flattening the histogram distribution. However, this method is sometimes non-optimal because the calculations carried out are global. AHE is a refinement of HE, which has the advantage of being more adaptive in calculating the histogram distribution. However, AHE sometimes has a weakness in determining the threshold for contrast values. This weakness is enhanced by CLAHE by dividing the image into smaller areas, to obtain an optimal contrast value. Unfortunately, CLAHE has a weakness in computational time.

Figure 1. The finger vein-based authentication process.

![Figure 1](image1)

Figure 2. The various contrast condition on finger vein NIR images.

Sheet [4] in 2010 developed a hybrid method called Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE). BPDFHE method was developed to improve image contrast and brightness quality with a relatively short computation time. Seeing the advantages possessed, this study proposed the use of the BPDFHE method to improve the contrast quality of finger vein NIR images. As a comparison material for performance tests, the HE, AHE, and CLAHE methods were also tested. The formation of this paper organized as follows; Section II described the methods. Section III presented the results and discussion, then succeeded by a conclusion and future work in Section IV.
2. Methods

2.1. Approach
This research was part of the IRVIN Project. IRVIN stands for fingervein imaging, aiming to design biometric studies based on the finger vein patterns. The first milestone was the segmentation process of the finger vein pattern, with the process flow as shown in Figure 3.

![Figure 3. First Milestone Flow of IRVIN Project.](image)

Based on Figure 3, the main focus of this study was the contrast enhancement stage, to examine the optimal contrast enhancement method in dealing with variations in contrast quality in the dataset.

2.2. Dataset
The dataset in this study was taken from The IDIAP Research Institute VERA Fingervein Database [5–7]. A total of 110 subjects presented their 2 indexes to the sensor in a single session and recorded 2 samples per finger with 5 minutes separation between the 2 trials. The database, therefore, contains a total of 440 samples and 220 unique fingers.

The dataset was composed of 40 women and 70 men whose ages were between 18 and 60 with an average of 33. The acquisition images are stored in PNG format, with a size of 250x665 pixels (height x width), and 8 bits of color depth. To set the region of interest (RoI), the original image then cropped 50 pixels on each side, and gain the cropped image with a size of 150x565 pixel (height x width), as shown in Figure 4.

![Figure 4. Original and RoI Image.](image)
2.3. **Contrast Enhancement Algorithms**

2.3.1. **Histogram Equalization (HE).** HE is an image processing algorithm which used to improve the image contrast in the spatial domain. It is one of the most commonly used because of its high efficiency and simplicity [8,9]. It achieved this by completely flattening out the most various intensity values. This method was valuable for images that were bright or dark.

2.3.2. **Adaptive Histogram Equalization (AHE).** AHE derived from HE that the adaptive method formulates each histogram of the sub-image to redistribute the brightness values of images. AHE was accordingly proper for enhancing the local contrast of an image and for bringing out more detail[10,11].

2.3.3. **Contrast Limited Adaptive Histogram Equalization (CLAHE).** CLAHE was originally developed to enhance the low-contrast medical images [12]. It is differing from ordinary AHE in its contrast limiting. Unlike HE, CLAHE works on small areas in the image and calculates some histograms, any corresponding to a different region of the image, and uses them to redistribute the image brightness value[10,13]. CLAHE restrained the amplification by cropping the histogram at a user-defined value called the clip limit. The clipping level defined noise level in the histogram should be smoothed, and hence the contrast level should be enhanced. In general, the mathematical expression for CLAHE showed in Equation (1).

\[ g = [g_{\text{max}} - g_{\text{min}}] \times P(f) + g_{\text{min}} \]  

(1)

\( g \) in Equation (1) is the computed pixel value, while \( g_{\text{max}} \) and \( g_{\text{min}} \) means of the maximum and minimum pixel value. \( P \) means cumulative probability distribution (CPD) of Rayleigh distribution which is given as Equation (2).

\[ y = P(f(x|b)) = \int_{0}^{\theta} \frac{x}{b^2} e^{-\frac{x^2}{2b^2}} \]  

(2)

2.3.4. **Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE).** BPDFHE was developed by Sheet [4], which was a modification method to adjust its brightness preserving and contrast enhancement capabilities while decreasing its computational complexity. BPDFHE uses fuzzy statistics of digital images for their representation and processing. The image representation and processing in the fuzzy domain permitted the method to deal with the inexactness of Gray-level values in a better way. The BPDFHE technique consists of four stages, as follows: 1) Fuzzy histogram computation; 2) Partitioning of the histogram; 3) Dynamic histogram equalization of the partitions; and 4) Normalization of the image brightness.

2.4. **Evaluation Parameters**

2.4.1. **Absolute Mean Brightness Error (AMBE).** AMBE is used to evaluate brightness preservation in the processed image. In simply, AMBE defines as Equation (3).

\[ \text{AMBE}(X, Y) = |\bar{X} - \bar{Y}| \]  

(3)

Based on Equation (3), \( \bar{X} \) refers to the mean of input image \( X = \{ x(i,j) \} \) and \( \bar{Y} \) is mean of the output image \( Y = \{ y(i,j) \} \). The smaller AMBE value indicated the better quality of the post-processing image.
2.4.2. Peak Signal to Noise Ratio (PSNR). PSNR is a parameter that is mostly used to measure the comparison of image quality before and after given the quality improvement. It can be calculated using Equation (4).

\[
PSNR = 10 \log_{10} \left( \frac{n^2}{MSE} \right)
\]  

(4)

Based on Equation (4), \(n\) refers to the maximum value of grayscale and MSE refers to Mean Square Error, a value of average error between the image before and after processing that can be counted using Equation (5).

\[
MSE = \frac{1}{MN} \left( \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (g(x,y) - g'(x,y))^2 \right)
\]  

(5)

Based on Equation (5), \(M\) and \(N\) mean of the image resolution, \(g(x,y)\) and \(g'(x,y)\) refer to the value before and after processing. Based on Equation (4), it can be showed that PSNR is inversely proportional to MSE. If the value of PSNR is high, then the quality of the image after processing will be better as the gain of the error is relatively low and vice versa.

2.4.3. Structure Similarity Index Measure (SSIM). The structural similarity index is a method for measuring the similarity between two images. The SSIM index is a measuring of image quality based on an initial uncompresed or distortion-free image as a reference. The range of the SSIM value is between 0 and 1. If it is getting closer to 1, then the enhancement process does not damage the structure of the image too much. SSIM can be calculated using Equation (6).

\[
SSIM(X,Y) = \frac{(2\mu_X\mu_Y + C_1)(2\sigma_{XY} + C_2)}{\mu_X^2 + \mu_Y^2 + C_1(\sigma_X^2 + \sigma_Y^2 + C_2)}
\]  

(6)

Based on Equation (6), \(\mu_X\) and \(\mu_Y\) refer to the mean of image \(X\) and image \(Y\) on each, while and \(\sigma_{XY}\) respectively means of the square root of covariance of image \(X\) and image \(Y\), and, are contents.

2.4.4. Feature Similarity Index Measure (FSIM). FSIM refers to a parameter used to measure the value of the image quality after experiencing the process of quality improvement, such as in an image run into the filtering process to remove the noise. This parameter will count the similarity between the image before and after enhancement. The range of values of FSIM is between 0 and 1. If getting closer to 1, then the process of quality improvement will be excellent as it has improved the image quality without damaging the features of the image[14]. FSIM can be calculated using Equation (7).

\[
FSIM = \frac{\sum_{x\in\Omega} S_L(x) \cdot PC_m(x)}{\sum_{x\in\Omega} PC_m(x)}
\]  

(7)

Based on Equation (7), \(S_L\) refers to the overall similarity between frequency image before processing \((f_1)\) and frequency image after processing \((f_2)\). \(PC_m\) denotes the phase congruency map, and \(\Omega\) means the whole image spatial domain.
3. Results and Discussion

In this section, we present some experimental results of our proposed method, together with HE, AHE, and CLAHE for comparison. Figure 5 shows the image result of each method. Table 1, Table 2, Table 3, and Table 4 present the experiment result for AMBE, PSNR, SSIM, dan FSIM on each, while Table 5 gives the computational time for each method.

![Figure 5](image)

**Figure 5.** (a) Original Image, Result Image of: (b) HE, (c) AHE, (d) CLAHE, (e) BPDFHE.

| Subject | HE Left Finger | HE Right Finger | AHE Left Finger | AHE Right Finger | CLAHE Left Finger | CLAHE Right Finger | BPDFHE Left Finger | BPDFHE Right Finger |
|---------|----------------|----------------|-----------------|-----------------|-------------------|-------------------|-------------------|-------------------|
| 1       | 4.328          | 18.509         | 6.2079         | 16.342         | 8.694             | 11.524            | 0.002             | 0.067             |
| 2       | 23.389         | 0.861          | 15.298         | 1.419          | 12.04             | 9.066             | 0.020             | 0.086             |
| 3       | 48.535         | 25.57          | 22.082         | 9.320          | 13.699            | 12.587            | 0.134             | 0.013             |
| ...     | ...            | ...            | ...            | ...            | ...               | ...               | ...               | ...               |
| 110     | 29.615         | 1.724          | 21.048         | 3.537          | 13.257            | 9.941             | 0.020             | 0.243             |
| AVG     | 23.082         | 9.608          | 8.428          |                |                   |                   |                   | 0.054             |

| Subject | HE Left Finger | HE Right Finger | AHE Left Finger | AHE Right Finger | CLAHE Left Finger | CLAHE Right Finger | BPDFHE Left Finger | BPDFHE Right Finger |
|---------|----------------|-----------------|-----------------|-----------------|-------------------|-------------------|-------------------|-------------------|
| 1       | 18.671         | 16.738          | 23.793          | 19.249          | 26.139            | 23.472            | 31.815            | 33.035            |
| 2       | 14.965         | 17.067          | 20.197          | 27.536          | 24.18             | 25.797            | 21.868            | 24.445            |
| 3       | 12.424         | 15.913          | 18.766          | 22.245          | 22.505            | 22.978            | 21.771            | 21.707            |
| ...     | ...            | ...             | ...             | ...             | ...               | ...               | ...               | ...               |
| 110     | 16.544         | 21.011          | 17.621          | 22.259          | 23.229            | 23.516            | 28.763            | 28.89             |
| AVG     | 18.932         | 26.134          | 26.432          |                |                   |                   |                   | 26.873            |
Table 3. SSIM Result.

| Subject | HE Left Finger | HE Right Finger | AHE Left Finger | AHE Right Finger | CLAHE Left Finger | CLAHE Right Finger | BPDFHE Left Finger | BPDFHE Right Finger |
|---------|----------------|-----------------|-----------------|-----------------|-------------------|-------------------|-------------------|-------------------|
| 1       | 0.655          | 0.745           | 0.707           | 0.692           | 0.921             | 0.905             | 0.920             | 0.966             |
| 2       | 0.668          | 0.590           | 0.664           | 0.665           | 0.910             | 0.927             | 0.851             | 0.870             |
| 3       | 0.677          | 0.697           | 0.669           | 0.650           | 0.911             | 0.917             | 0.869             | 0.786             |
| …       | …              | …               | …               | …               | …                 | …                 | …                 | …                 |
| 110     | 0.809          | 0.771           | 0.695           | 0.701           | 0.908             | 0.916             | 0.949             | 0.932             |
| AVG     | 0.628          | 0.692           | 0.925           | 0.840           |                   |                   |                   |                   |

Table 4. FSIM Result.

| Subject | HE Left Finger | HE Right Finger | AHE Left Finger | AHE Right Finger | CLAHE Left Finger | CLAHE Right Finger | BPDFHE Left Finger | BPDFHE Right Finger |
|---------|----------------|-----------------|-----------------|-----------------|-------------------|-------------------|-------------------|-------------------|
| 1       | 0.861          | 0.929           | 0.849           | 0.858           | 0.918             | 0.936             | 0.946             | 0.973             |
| 2       | 0.883          | 0.833           | 0.819           | 0.816           | 0.931             | 0.924             | 0.898             | 0.900             |
| 3       | 0.911          | 0.860           | 0.817           | 0.768           | 0.911             | 0.911             | 0.905             | 0.832             |
| …       | …              | …               | …               | …               | …                 | …                 | …                 | …                 |
| 110     | 0.963          | 0.924           | 0.839           | 0.848           | 0.944             | 0.941             | 0.968             | 0.959             |
| AVG     | 0.856          | 0.847           | 0.929           | 0.906           |                   |                   |                   |                   |

Table 5. Execution Time Consumed (in seconds).

| Method | Total Time |
|--------|------------|
| HE     | 15.048     |
| AHE    | 20.302     |
| CLAHE  | 1717.638   |
| BPDFHE | **10.988** |

In Table 1, the BPDFHE method can produce the smallest AMBE value, while the HE method gained the highest AMBE value. It was related based on the PSNR results in Table 2. The best PSNR values were generated by the BPDFHE method and the HE method achieves the worst PSNR values. It mean that BPDFHE is effective in improving the contrast quality of finger vein NIR images. This result was influenced by the fuzzy method used to map the distribution of pixel intensity so that it can be more even.

The SSIM and FSIM test results in Table 3 and Table 4 show that CLAHE has the best performance and the worst was the HE method. These results indicate that CLAHE can maintain the quality of the image structure and features well, which was also supported by the visualization in Figure 5d. It show that the image processed by CLAHE did not change in visualization significantly. In Figure 5b, it appeared that the image resulting from the HE method has significant changes, and it related to the image structure.

Although the BPDFHE gained a lower performance than CLAHE, it still in good condition, with SSIM and FSIM values of 0.840 and 0.906 on each. Visually, in Figure 5e, there was a change in several areas of the image, so that the image structure change slightly compared to the results of the HE methods (Figure 5b) and AHE (Figure 5c).

Execution time testing was highly dependent on hardware and software conditions. For the hardware, it used the 5th Generation Intel Core i5-5200U2.2GHz of CPU and 8GBDDR3 of RAM, while for the software, it used Windows 10 as an operating system and the MatlabR2020a as a framework. Table 5 shows that the BPDFHE produces the shortest computation time, as long as...
10.988 seconds. Meanwhile, CLAHE has the longest computation time, as long as 1717.638 seconds. BPDFHE gained less computation time due to the influence of the fuzzy method in handling the uncertainty condition of the histogram value. CLAHE performance was not good because it depended on the size of the image resolution. The larger the image size, the longer CLAHE takes for the computation and vice versa. Based on this result, even though CLAHE gained the best SSIM and FSIM values, the overall resulting performance was less than optimal because it required a longer computation time.

4. Conclusion

Based on the result of the test, it is concluded that the BPDFHE method, as a proposed method, was able to provide the most optimal performance compared to the other four methods. BPDFHE can maintain brightness stability, improve contrast quality effectively, and has a relatively short computation time.

In the next investigation, the research will focus on the finger vein pattern extraction by applying the noise reduction, thresholding, and skeletonization process in advance.

Acknowledgment

This work is supported by the Department of Research Institutions and Community Service, Universitas Pendidikan Ganesha (grant number: 692/UN48.16/LT/2020).

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