Radiographic X-ray Images Enhancement with Edge Preservation using Singular Value Decomposition

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Abstract: Contrast enhancement is one of the important issues in Medical X-ray imaging since these image, in general, are of low contrast and luminance. In medical X-ray imaging system viewing the bone structure and soft tissues are important for better medical diagnosis. The accuracy of Medical diagnosis of a patient purely depends on the clarity of the image. Hence an X-ray image must be well enhanced at the same time edges must be preserved and highlighted while applying image pre-processing technique. This is a challenging task in literature. In literature many techniques had been proposed for improving the low contrast images in various applications like satellite images, medical images, etc. Standard methods include General Histogram Equalization (GHE), Local Histogram Equalization (LHE), AHE or CLACHE, Brightness Preserving Histogram Equalization (BBHE), etc. All these methods rely on histogram equalization on the entire image, might lead to loss of edge information. Since Soft-Tissues and bone pixels have similar values, global equalization methods might fail. So to resolve these challenges, this paper presents a new method using Singular Value Decomposition (SVD) for image enhancement and also improves the edge quality. Proposed method works in two phases: background suppression and foreground enhancement. The proposed method decomposes the X-ray image using SVD and extracts the singular values of the image (which represents the order of luminance in the image). These singular values are further analyzed to identify the highly dominating singular values and are used for background suppression. Later the foregrounds, i.e., the bone pixels are enhanced through histogram equalization. Advantage of the proposed method is shown experimentally using various images like a hand, pelvic, skull and chest of a human. As standard matrices, PSNR, SNR, and Entropy focus on complete enhanced image (i.e., foreground and background) might fail to justify the improvement in enhancement. Thus, in this paper performance is evaluated using standard texture metrics: homogeneity, contrast, entropy, mean and standard deviation. Results of the proposed method are compared with standard literature methods like AHE, CLACHE, MMBEBH, and BHE. The proposed method has shown the better results with highest homogeneity (0.88), lowest contrast (0.32), highest correlation (0.97), and highest energy (0.21). Edge preservation accuracy is also highest (i.e., 0.98%) in comparison to literature methods.

Keywords: Singular Value Decomposition (SVD), Image Equalization, Homogeneity, Contrast, Correlation, PSNR, SNR, Standard Deviation, Energy.

1 Introduction

Medical imaging system is a study of a living body organism and its properties for diagnosis and treatment. Common imaging systems include X-ray, MRI, CT, etc. These images are digitized for doctor/specialist analysis. This paper concentrates on X-ray images only. Wilhelm Conrad Roentgen, a professor at Wurzburg University in Germany, discovered these X-rays in 1895 [1]. Medical X-rays travel through the human body to be received at X-ray detector and generate an image of the internal bone structure of a human/patient. The basic X-ray detector is a photographic film (hard copy). After digitizing they are called radio-graphs. These X-ray images are produced with three different tissues such as bone tissue, soft-tissue and background because the absorption rate is different for different tissues. The calcium in bone absorbs the rays in highest thus leading to bones tissues in white pixels, while fat, and background absorb fewer rays thus leads to gray and black pixels.
Medical x-ray imaging is widely used in verifying bone disorders, bone fractures, bone cancer, and early stage cancer detection in mammograms (chest). They are also used to detect mammographic tumours in the breasts. X-rays are generated through transmission of electromagnetic radiation waves with deferent wavelengths and frequencies. This spectrum is divided into seven regions such as radio waves, microwaves, infrared waves, visible light waves, ultraviolet, x-ray, and gamma rays. These radiations are high in frequency and short in wavelength, frequency ranging from $10^{16}$ to $10^{20}$ hertz (Hz) and wavelength from $10^{-8}$ to $10^{-12}$ meter, same is depicted in Figure 1.

A radiographic image contains tissues representation with a wide variety of textures and depths. Due to which the x-ray image gets variations in luminance and contrast. These medical images may also be prone to electronic noise which results in degradation in the quality of the image. All these may affect the appearance of the image; hence new approaches need to be developed for suppressing these challenges. To resolve these challenges, many scientists have proposed different methods in the literature [3-10].

2 Literature Review

Several techniques had been proposed in the literature for improving the low contrast images in various applications like satellite images, medical images, etc. The basic methods include General Histogram Equalization (GHE) [3], Local histogram equalization (LHE) [4]. Unsharp masking technique is used for edge enhancement applications [5, 6, 7]. The noise removal is done through median or means filtering [8] and edges are sharpened by unsharp masking and followed by HE, AHE or CLACHE [9]. Another method for contrast enhancement is based on brightness preserving contrast improvement. Kim has proposed a method Brightness Preserving Histogram Equalization (BBHE)[10].

Here the image is divided into multiple sub-images based on histogram counts and a separate Histogram equalization is been applied. Wang and et al. [11] proposed Dualistic sub-image Histogram Equalization (DSIHE) method, where the image is divided into two sub-images and equalized individually. Another approach named Minimum Mean Brightness Error Bi-Histogram Equalization was proposed by Chen and Ramli [12]. If contrast enhancement is based on histogram count, details of the image might get lost. Thus during the last few decades, Discrete Wavelet Transform (DWT) has emerged widely along with singular value decomposition (SVD) for image enhancement. DWT and SVD are widely used in image noise
removal, image compression and image enhancement [13, 14]. These methods can be further enhanced with better improvements. Hence this paper proposes a new technique using SVD and Histogram Equalization for contrast enhancement.

3 Proposed Method

This paper proposes a new method to enhance the X-ray images using SVD. Here SVD is used to extract the features of foreground pixels and suppress the background pixels of the X-ray image. Then foreground pixels are enhanced using histogram equalization. Figure 2 demonstrates the details of the algorithm.

3.1 Singular Value Decomposition (SVD)

SVD has widely been used for past few years in the applications of noise suppression and face recognition, etc [15]. SVD states that any given rectangular matrix \( A \) of size \( m \) rows and \( n \) columns can be represented as in the form \( USV^T \) as in Eq. (1).

\[
A = USV^T \tag{1}
\]

Here \( U \) is an orthogonal matrix of the form \( m \times m \).

\[
U = [U_1, U_2, \ldots U_r, U_{r+1}, U_{r+2}, \ldots U_m] \tag{2}
\]

Matrix \( V \) is an \( n \times n \) orthogonal matrix

\[
V = [V_1, V_2, \ldots V_r, V_{r+1}, V_{r+2}, \ldots V_n] \tag{3}
\]

And \( S \) is a diagonal matrix of size \( m \times n \) having singular values of matrix \( U \) or \( V \).

\[
S = 
\begin{bmatrix}
\sigma_1 & 0 & 0 & 0 & 0 \\
0 & \sigma_2 & 0 & 0 & 0 \\
0 & 0 & \sigma_3 & 0 & 0 \\
0 & 0 & 0 & \ddots & 0 \\
0 & 0 & 0 & 0 & \sigma_n
\end{bmatrix} \tag{4}
\]

Where \( \sigma_i \) are the singular values and stored in descending order from \( \sigma_1 \) to \( \sigma_n \). Hence finally \( A \) is represented as follows:

\[
A = \sum_{i=1}^{n} U_i \sigma_i V_i^T \tag{5}
\]

3.2 Foreground Enhancement

The proposed method first applies SVD on the given image and \( U \), \( V \) and \( S \) matrices are identified. Here matrix \( S \) play an important role as it is the matrix of Eigen values describing its important luminance features in descending order. Non-edge details are not required for image enhancement, should be removed from the image completely for better image enhancement. Proposed method identifies the prominent singular values in the image and enhances only these prominent pixels by suppressing the remaining (indicating the background or non-important features in the image).

Radiographic X-ray image matrix is converted to singular value decomposition to extract the singular values in the matrix \( S \). These \( S \) diagonal elements are copied to temporary array \( S1 \). Further from \( S1 \) the neighbouring with its corresponding column vectors of \( U \) and \( V \) matrices as per Eq. (5). Now the reconstructed image \( RI \) will hold high values for foreground and low
values in the non-foreground locations. Hence a threshold 'T' can be used to differentiate them (T varies for different types of X-ray images). The image FGImg image is further enhanced using histogram equalization. Thus finally FGHE and RI are merged to show the final foreground enhancement. Algorithm 1 presents the working of foreground enhancement process.

4 Experimental Results and Discussion

Figure 3 (a) to (c) represents the original images on which the algorithm is applied. Next Figure 3 (d) to (f) represents the separation of foreground and background using SVD and Figure 3 (g) to (i) shows the final results of enhancement. Final enhanced images are sufficiently clear with background removal and highlighted foreground. Figure 4 shows the result of the proposed method applied to different types of X-ray images and compares the results with the existing methods.

![Proposed Model Representation](image)

Figure 2. Proposed Model Representation
Algorithm 1: X-ray Image Enhancement

Input: X-ray Image I of size M×N
Output: EnhImg

Ensure:
1. $\theta$ is a variable parameter
2. $T$ is a Threshold
3. $j \leftarrow 0$

1: $[U, S, V] \leftarrow$ SVD (I)
2: $S1 \leftarrow$ Extract_Diagonal_Elements (S)
3: for $i \leftarrow 0$ to (size (S1)−1) do
4: if mod $(S1(i) − S1(i+1)) > \theta$ then
5: $S11(j) \leftarrow S1(i)$
6: $j \leftarrow j + 1$
7: end if
8: end for
9: $R1 \leftarrow U' \times S11 \times V'$
10: for $i \leftarrow 1$ to M do
11: for $j \leftarrow 1$ to N do
12: if $R1(i, j) > T$ then
13: $FGImg(i, j) \leftarrow R1(i, j)$
14: else
15: $FGImg(i, j) \leftarrow 0$
16: end if
17: end for
18: end for
19: FG_HE $\leftarrow$ Hist_Equalization(FGImg)
20: EnhImg $\leftarrow$ merge(FG_HE, R1)
21: return EnhImg

4.1 Performance Analysis

Proposed method has been implemented using MATLAB. Performance of the proposed method can be evaluated using PSNR, SNR, and Entropy as in literature [16]. These methods can be applied when the image enhancement is focused on the entire range of pixels of the image. In the proposed work the background pixels are suppressed, and foreground pixels have been enhanced. Thus the PSNR, SNR, and Entropy will fail to justify the enhancement improvement of the image. Hence the proposed method’s performance is evaluated using texture improvement properties stated in [17]. Texture Properties are Homogeneity, Contrast, Correlation, and Energy. Each one has its own identity to prove. All these properties are estimated first generating Gray Level Co-occurrence Matrix (GLCM). It is estimated using Lemma 1. Homogeneity measures the distribution closeness among the pixels of GLCM matrix to its diagonal elements (represented in Eq. (7)).

Lemma 1- GLCM is the matrix, with total counts all pairs of gray level pixels, $l2$ displaced by a factor d. Where d is the displacement vector = (dx, dy).

Contrast measures the variations in gray level co-occurrence matrix stated in Eq. (8). Correlation measures the neighbouring pixels correlation. Energy measures the squared sum of GLCM elements. These two properties are
Figure 3. Foreground Enhancement Applied on X-ray images (a) to (c) are original images, (d) to (f) are background suppressed images and (g) to (i) are enhanced images.

stated in Eq. (9) and Eq. (10). Homogeneity will be high i.e., 1 for a plane image where the image is of a same texture, while contrast will be near to zero in the case of a uniform image.

\[ P(i,j) = \frac{C(i,j)}{\sum_{i,j=1}^{N} C(i,j)} \]  \hspace{1cm} (6)

Here \( C(i,j) \) is each cell value of GLCM, N the number of rows and columns.

\[ \text{Homogeneity} = \sum_{i,j=1}^{N} \frac{p(i,j)}{1 + |i - j|} \]  \hspace{1cm} (7)

\[ \text{Contrast} = \sum_{i,j=1}^{N} p(i,j)(i - j)^2 \]  \hspace{1cm} (8)

\[ \text{Correlation} = \sum_{i,j=1}^{N} \frac{(i-\bar{i})(j-\bar{j})p(i,j)}{\sigma_i \sigma_j} \]  \hspace{1cm} (9)
Energy = $\sqrt{\sum_{i,j=1}^{N} P(i,j)^2}$  \hspace{1cm} (10)

Table 1 depicts the performance comparison of the proposed method with Bi-Histogram Equalization (BHE), Adaptive Histogram Equalization (AHE), Contrast Limited Histogram Equalization (CLAHE), Minimum Mean Brightness Error Bi-Histogram Equalization (MMEBEBHE). For this study, 100 X-ray images were used from the data source provided by IRMA (Image Retrieval in Medical Applications) [18]. This dataset contains the X-rays of hand, pelvic, skull, and chest. Figure 5 shows a comparison of average values of literature methods and the proposed method. Here proposed method depicts the higher homogeneity and correlation value. Figure 6 shows the average values of contrast and energy. As contrast should be minimum for the better equalized image, proposed method shows the same with 0.3 contrasts. Energy should be maximum for good enhanced image; proposed method shows high energy in comparison to others.

Metrics for comparing the contrast improvement are mean and standard deviation among pixels of the image. Table 2 shows the means and standard deviations after applying existing methods and the proposed method for an image with original mean 130.9 and standard deviation 18.60. Mean of an image denotes the brightness and standard deviation denotes the contrast of the image. Table 2 shows the contrast improvement of a single image where CLACHE, AHE, BHE, and MMEBEBHE had high brightness but, the contrast is very low. In contrast, the proposed method shows the mean brightness 129.3 but has very good contrast enhancement with 73.43. Table 3 tabulates the average mean and standard deviation values of the proposed method and literature methods. Here the mean and standard deviation of the proposed method is better in comparison to others. Figure 7 depicts the same in a bar chart.

Proposed Method has shown the image enhancement to be better than the AHE, BHE, CLACHE and MMEBHE methods. The existing methods focus on equalizing the entire image irrespective of background and foreground objects. Thus can lead to miss-classification of edges within the objects and might generate new edges in background locations. Proposed method focuses on enhancing only the dominating features i.e., the only foreground. Thus edges of x-ray image are enhanced only within the foreground region, unlike the existing enhancement methods. Figure 8 shows the original and final enhanced image. Figure 9 from (a) to (l) shows the Comparison of Gradients in original image and enhancement methods.

Table 1. Average values of Homogeneity, Correlation, Contrast and Energy of proposed method with literature methods.

| Method   | Homogeneity | Correlation | Contrast | Energy  |
|----------|-------------|-------------|----------|---------|
| Original | 0.9302      | 0.9768      | 0.1421   | 0.1872  |
| CLACHE   | 0.7424      | 0.7797      | 1.1745   | 0.0813  |
| AHE      | 0.8258      | 0.9431      | 0.4148   | 0.1083  |
| BHE      | 0.7692      | 0.8167      | 1.6394   | 0.0773  |
| MMEBEBHE | 0.8435      | 0.9482      | 0.4840   | 0.0942  |
| Proposed | 0.8888      | 0.9734      | 0.3257   | 0.2195  |
Figure 4. Comparison of Proposed results with state-of-the-art approaches
Figure 5. Comparison of Homogeneity and Correlation among all methods

Figure 6. Comparison of Contrast and Energy among all comparison methods

Figure 7. Comparison of Mean and Standard deviation among the literature methods with proposed method.
**Figure 8.** Comparison of original and enhanced image

| Method              | MEAN  | STD  |
|---------------------|-------|------|
| Original            | 99.71 | 60.46|
| CLACHE              | 119.37| 52.57|
| AHE                 | 106.67| 63.42|
| BHE                 | 142.16| 69.56|
| MMEBEBHE            | 126.99| 70.99|
| Proposed            | **86.42** | **83.12** |

**Table 2.** Comparison of Average Mean and Standard deviation among literature methods and proposed method
Conclusion

Radiographic X-ray image enhancement is demanding in the field of medical imaging. The accuracy of Medical diagnosis of a patient purely depends on the clarity of the image. This paper focuses on image enhancement and proposes a novel approach. Here the image enhancement is achieved using Singular Value Decomposition (SVD). SVD extracts the singular values of the image which are in the sorted order. The proposed method studies these singular values and selects the prominent luminance values to reconstruct the image by suppressing the background and unwanted edges. The proposed method results are compared with most popular algorithms BHE, AHE, CLACHE, and MMEBHE for verifying the contrast enhancement. Proposed method has shown the better results with high homogeneity, low contrast, high correlation and high energy values of texture properties in comparison with other methods. In future method can further be extended for complete automations of singular value reduction with deep study of data analysis approaches.

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