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Contrast enhancement for cephalometric images using wavelet-based modified adaptive histogram equalization

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ABSTRACT

Cephalometric images usually have low contrast. The existing techniques for automatic cephalometric analysis usually use histogram equalization for image enhancement. This technique has the advantage of being fully automatic and nonlinear. However, it suffers from spikes, excessive enhancement, and lack of brightness preservation. The proposed technique is an adaptive histogram equalization technique that uses wavelet based gradient histograms. This paper compares its performance with two traditional techniques, three histogram modification based techniques, and two wavelet based techniques. Forty digital and scanned cephalograms are used to conduct tests. In addition to visual histograms and intensity profiles, the proposed method is compared in terms of eight quantitative measures. The various measures are applied to analyze the results in terms of contrast enhancement (EME, CNR), brightness preservation (AMBE), edge conservation and enhancement (H, TEN), preservation of image structures and non-addition distortion (MSSIM, SVD-M). The proposed method gives good contrast enhancement, with better brightness preservation without losing edge information and with the minimum addition of distortions to the enhanced cephalometric images.

1. Introduction

X-ray images have reduced contrast and visibility of small objects because of high X-ray penetration, scattered radiations, blurring and the limited capacity of films to develop the maximum contrast. Cephalometric images of skull consisting of bony structure and soft tissue details suffer from blurring due to nonparallel radiations. Anatomical areas of gradual change lead to blurring of edges. Patient moment may cause motion blur [1]. Other characteristics that influence the quality of X-ray images are unique to the capturing approach. X-rays convert to image information using one of the three methods: a film detector, image intensifier and direct digital methods [1,2]. In X-ray films, captured using the film detector, the contrast is less in high and low-density areas. Scanning X-ray films for digitizing add noise to scanned images. Image intensifier adds noise because of change from light to photons and the other way around. The produced X-rays images suffer from distortions toward the borders. Direct digital methods give lower *signal-to-noise-ratio* (SNR) than film detector and image intensifier methods [2].

Increased contrast improves visual perception and diagnostic information in cephalograms. The computer-aided cephalometric analysis gives better result with sharper cephalograms. Further, repeated X-ray exposures of patients may lead to cancer. Image enhancement methods may help to avoid retakes and multiple exposures of the patients.

In this paper, we propose a contrast enhancement technique that uses biorthogonal spline wavelets to identify the edge pixels and discard the pixels in homogeneous regions while computing image histograms. The modified algorithm is used with *contrast limited adaptive histogram equalization* (CLAHE) to reduce spikes and improve its overall performance.

The organization of the paper is: An overview of contrast enhancement techniques and related work is presented in Section 2. Section 3 discusses preliminary and the proposed algorithm. The experimental results and discussions are demonstrated in Section 4. Finally, Section 5 and Section 6 presents the summary and conclusions respectively.

2. Related work

Histogram equalization (HE) is an automatic and straightforward contrast improvement technique. Thus, most of the existing literature on contrast enhancement of cephalograms use histogram

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equalization. Tong et al. [3] applied histogram equalization to increase the range of gray levels in an image. Sanei et al. [4] pre-processed the X-ray image by segmentation of the histogram to highlight soft tissue and bony structure. Eli-Feghi et al. [5] applied histogram equalization followed by the median filter of size 5×5 to enhance the image. Frosio [6] presented a technique called soft tissue filter using histogram clustering and gamma correction for the enhancement of cephalometric radiographs. Favaedi and Maria et al. [7] applied local histogram equalization followed by Canny edge detection [8] to isolate the edges.

The traditional histogram equalization is a global technique, which sometimes leads to excessive contrast enhancement. Spikes occur because of the presence of similar pixels in the homogeneous regions. Spikes increase noise, add artifacts and changes image histogram, resulting in unnaturally looking images. Many papers propose regularization to avoid excessive enhancement. Global HE does not preserve the brightness that leads to washed appearance of some pictures [8]. Several advanced HE methods are proposed to prevent a change in image brightness, over enhancement and addition of artifacts.

2.1. Brightness preserving techniques

Kim [9] introduced bi-histogram equalization to preserve the brightness by separating the histogram of the image into two parts based on mean gray level. Chen and Ramli [10] improved [9] by using the minimum *absolute mean brightness error* (AMBE) to estimate the threshold to partition the histogram. Sengee et al. [11] presented an extension to [10] with neighborhood metrics. Zuo et al. [12] developed a contrast enhancement technique referred to as *range limited bi-histogram equalization* (RLBHE). In this technique, to separate the objects from the background, the histogram divides into two independent sub-histograms by a threshold to minimize the inter-class variance. Finally, calculates the range to minimize AMBE between the original and equalized histograms. Similarly, Huang and Yeh [13] divides the histogram into sub-histograms to achieve contrast modification. A technique proposed by Rajavel [14] uses curvelet transform and histogram matching for increasing the image contrast. Hashemi et al. [15] described a method based on genetic algorithm to improve contrast. The method is suitable for consumer electronic products. Atta and Abdel-Kader [16] used singular value decomposition for contrast enhancement. The technique gives enhanced images without the addition of artifacts and change in mean brightness of the image.

2.2. Techniques robust against over enhancement and artifacts

Ooi et al. [17] developed a hybrid of the bi-histogram equalization and clipped histogram equalization to overcome unwanted over-enhancement and noise amplification. Abdullah-Al-Wadud et al. [18] partition the histogram into sub-histograms based on the local minima of the smoothed histogram. The algorithm assigns a specified gray level range to each partition and equalizes them separately. However, it does not preserve the image brightness. Ibrahim and Kong [19] improved [18] for brightness preservation. Sheet et al. [20] proposed brightness preserving fuzzy histogram equalization. Yan-feng et al. [21] developed a double-plateau HE using two thresholds, the upper threshold to constrain background noise and a lower threshold to protect and enhance the details. Wang and Ward [22] presented weighted threshold histogram equalization. Jha et al. [23] developed a technique to improve the contrast of dark images by using noise addition and thresholding. Sundaram et al. [24] described a technique called histogram modified local contrast-enhancement to enhance mammogram images. Celik [25] proposed a *two-dimensional histogram equalization* (2DHE) algorithm that utilizes contextual information around each pixel to increase the contrast. Han et al. [26] developed a 3D colour histogram equalization method using a new cumulative probability density function.

2.3. Wavelet based techniques

Applying wavelet transform to an image concentrates energy in a small subset of the wavelet coefficients, mostly along the edges. This feature is useful in image processing applications. Some contrast enhancement algorithms use wavelets to improve the image contrast. Yang et al. [27] proposed a technique (referred as WAV1 in the paper) to enhance the contrast of medical images by using Haar wavelet and histogram stretching. Wan [28] reported a method (referred as WAV2 in the paper) using Daubechies wavelets and exact histogram equalization. In [29] the authors have proposed a method for colour image contrast enhancement by combining bilateral filtering and exact histogram equalization using wavelet coefficients.

2.4. Local histogram equalization techniques

The properties of pixels vary spatially, thus using a single global histogram mapping does not enhance the local contrast optimally. In medical imaging local details are important. Local histogram approach working on small sub-windows is effective in such applications. Ketcham et al. [30] were the first to propose a local technique called *adaptive histogram equalization* (AHE). This method first divides the image into blocks, then mapping functions for each block is used to improve the contrast. The main disadvantage of this approach is slow speed and the presence of histogram spikes. The variation of this approach CLAHE [31] overcomes over-enhancement and noise amplification by clipping spikes and also improves computation speed. Another recent method [32] uses modified octagon histogram for contrast enhancement. The method gives comparable performance to AHE.

2.5. Contrasted-pixel based techniques

Some techniques instead of using all the pixels in the image consider only the edge pixels for computing histograms. Chen [33] proposed a *gray-level grouping* (GLG) technique based on grouping and ungrouping of histogram bins to avoid histogram spikes. Arici et al. [34] presented, a low complexity *histogram modification framework* (HMF) that adjusts the enhancement adaptively. Pixels based on the horizontal variation measure are considered to get a histogram. The modified histogram is computed using the weighted average of histograms and uniform histogram. Zeng et al. [35] proposed a new form of the histogram called the *gray level information histogram* (GLIH). In their technique, they divide the image into several regions according to the intensities of gradients. The summation of all the weighted values of regions give processed histogram.

In this paper, we propose a technique using *AHE with gray level information histogram using wavelet* (AGLIHW) for contrast improvement of cephalograms. Compared with related work, this method simultaneously improves the contrast between the skeletal structure and background and also between soft tissue and background. Further, the proposed method preserves and improves edges. High homogeneous areas in cephalograms lead to histogram spikes that increases noise and distortion present in cephalograms on applying HE. In the proposed algorithm biorthogonal spline wavelets identify the edge pixels, which carry image information. Pixels in homogeneous regions are discarded while computing image histograms. Non-consideration of homogeneous pixels help in reducing histogram spikes. The introduction of modified histogram for contrast enhancement of images in CLAHE improves its overall performance. The proposed approach uses modified CLAHE, gray level information histogram, and biorthogonal spline wavelets. The following sections discuss these topics briefly.

3. Preliminary

3.1. Contrast limited adaptive histogram equalization

The procedure followed by this method:

i. The image is divided into blocks.
ii. Histogram is extracted for each block.
iii. The derived histogram for each block is clipped and renormalised.
iv. The desired mapping function is calculated only at a sample of pixels and the mapping function for other pixels is obtained by interpolating mapping functions associated with its four neighbouring blocks.
v. The mapping functions are applied to get a contrast enhanced image.

Clipping and renormalization of the histogram reduce noise amplification and ringing artifacts. Interpolation helps to improve the speed of AHE. CLAHE uses the traditional histogram-based technique. The results are sensitive to histogram spikes. Thus, the performance of CLAHE can be significantly enhanced by reducing spikes. Histogram modification technique to reduce spikes is discussed in the next section.

3.2. Modified gradient based histogram

In GLIH [35] the input image is partitioned into several regions as per the image gradients. Summation of all the weighted regional histograms provide the processed histogram. Amplitudes of this new form of the histogram reflect the contribution of the gray levels to image edges and textures.

The present work is influenced by the method suggested in [35]. However, our technique differs significantly from [35]. In [35] Gaussian smoothing is applied to reduce the image noise and Sobel operator to compute the image gradients. In cephalograms, edges are blurry Gaussian smoothing further blurs the edges. Sobel's operator is unable to differentiate between the edge pixels and the image noise. Therefore, both these operators are unsuitable for use in cephalograms. With wavelets, the image gradient extraction and noise suppression is handled in a single step with better control of noise. Accordingly, in the proposed algorithm we use biorthogonal spline wavelets to identify the edge and texture pixels and discard the pixels in homogeneous regions while computing image histograms. It helps in reducing histogram spikes. The modified algorithm is used with CLAHE and improves its overall performance. Unlike [35] that use the Canny edge detector to find the edge pixels, the proposed algorithm removes this overhead by using wavelet based gradient information to find edge pixels.

3.3. Biorthogonal wavelet transform

The down sampling of the wavelet coefficients in *discrete wavelet transform* (DWT) causes shift variance [36]. DWT suffers from aliasing effects owing to down-sampling and may lead to artifacts in the reconstructed image. Thus, DWT is unsuitable for edge detection and pattern recognition. *Stationary wavelet transform* (SWT) is justified in such applications. SWT is identical to DWT in the decomposition structure except that no down-sampling is involved. The key features of this transform are that it is redundant and shift invariant and do not suffer from aliasing effects. These properties help in the efficient edge localization [37].

Wavelets are of two types, orthogonal and biorthogonal. Orthogonal wavelets employ one scaling and one wavelet function. However, these wavelets are often irregular and implicitly defined. Thus, implemented using *infinite impulse response* (IIR) filter banks. Wavelets with desirable properties are developed by removing orthogonality constraints [37–39].

Cohen et al. [40] introduced biorthogonal wavelet by eliminating the orthogonality requirement. In biorthogonal wavelets, two scaling and two wavelet functions are required. Biorthogonal wavelet pairs are symmetric, regular and compactly supported [41]. Thus, implemented using *finite impulse response* (FIR) filters. Compact support helps improve the computational complexity of the transform. Symmetry property of the filter coefficients is desirable since it results in linear phase transfer function. In image processing, the linear phase filters produce fewer visual artifacts [37–39]. The proposed technique uses biorthogonal spline wavelets owing to their explicit representation (piecewise polynomials) that makes the computation easier [41,42].

3.4. Proposed algorithm

The proposed algorithm first, divides the image into several subimages. Next, a modified histogram is computed for each block by using wavelet detail coefficients and statistical weights. The modified histogram is clipped before finding a mapping function from each histogram. A transformation function is obtained by interpolating the four neighbouring mapping functions. This transformation function is used to compute the pixel values in the enhanced image.

Algorithm. **Step I:** The image is divided into 16 equal sized blocks $b(x, y)$ of size $m \times n$.

Step II: For each block, a modified histogram, cumulative density function, and a mapping function is derived using the following procedure:

i. Wavelet-based gray level information histogram constructed as follows:

a) Apply SWT on each block until level two using biorthogonal spline wavelets. It results in a set of two approximation coefficients and six detailed coefficients. Select level two horizontal coefficients $W_\psi^H(x, y)$ and vertical coefficients $W_\psi^V(x, y)$ to extract gradient information as follows:

$$W_\psi^H(x, y) = \frac{1}{mn}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} b(x, y)\,\psi(x)\,\phi(y). \tag{1}$$

$$W_\psi^V(x, y) = \frac{1}{mn}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} b(x, y)\,\psi(y)\,\phi(x), \tag{2}$$

where ψ corresponds to the wavelet function and ϕ to the scaling function. Using the horizontal and vertical coefficients the gradient $G(x, y)$ is found by

$$G(x, y) = |Wd_\psi^H(x, y) + W_\psi^V(x, y)|. \tag{3}$$

b) Each block divides into *four* different regions based on the values of $G(x, y)$ and the three threshold values (Th_1, Th_2, Th_3). The three thresholds are computed automatically by using the first, second and third quartile of $G(x, y)$ respectively. The block is divided into four regions based on the following conditions:

IF the value of $G(x, y) \le Th_1$ THEN *pixel*(x, y) belongs to region one

ELSE IF the value of $Th_1 < G(x, y) \le Th_2$ THEN *pixel*(x, y) belongs to region two

ELSE IF the value of $Th_2 < G(x, y) \le Th_3$ THEN *pixel*(x, y) belongs to region three

ELSE *pixel* (x, y) belongs to region four

A separate histogram stored in h_m is computed for each of the *four* regions.

c) Weights $w(i)$assigned to each sub-histogram i are based on the number of edge pixels *count* (i) present in the corresponding region *i*. To generate the weights the number of edge pixels in each region is normalized by using the maximum value of *count* (i) we get the values of weights as

$$w(i) = count(i)/\max\_count. \tag{4}$$

d) The modified histogram H_m is the weighted sum of the four sub-histograms

$$H_m(l) = \sum_i h_m(l, i)w(i), \tag{5}$$

where $l = 0, 1, 2, 3.......L-1, L-1$ is the maximum intensity value in the image and $i = 1, 2, 3, 4, \ldots$.

ii. The modified histogram is clipped using a clip limit

a) Calculate the total number of pixels above clip limit in each histogram bin and sum them to get excess pixels.

b) The excess pixels are redistributed equally in all histogram bins.

c) If redistribution of excess pixels pushes some bins above the clip limit, steps a and b above, are repeated recursively till the excess pixels are zero.

d) The mapping function is derived using the cumulative density function of the clipped modified histogram H_m and stored as a lookup table.

Step III: The procedure in Step II repeats for computing mapping functions for each block.

Step IV: The derived mapping function enhances the centre pixels in each block. For other pixels, transformation functions obtained by interpolating four neighbouring mapping functions.

Step V: The derived mapping functions are applied to get the contrast enhanced image.

From multiple trials, we found that for cephalometric images, dividing each block into four regions and taking level two for wavelet decomposition gives the best results. The clipping limit is set to 0.002. Higher clip limit gives better contrast enhancements, but adds artifacts to the image, and lower values reduce the contrast enhancement.

4. Results and discussions

All the contrast enhancement methods are implemented in a MatLab environment on a PC with 2.5 GHz CPU and 4 GB RAM. The algorithm was tested using 20 digital (544×456) and 20 scanned (496×400) cephalograms of different quality. Cephalograms are grayscale images with depth of 8 bits. The performance of the proposed algorithm is compared with two traditional techniques HE [8] and CLAHE [31], two wavelet based techniques WAV1 [27] and WAV2 [28] and three other promising techniques namely GLG [33], HMF [34], GLIH [35]. Both subjective results in the form of visual images and quantitative results are presented.

4.1. Quantitative metrics

The following quantitative metrics are used for comparing the results:

- *Measure of enhancement by entropy* (EME) [43] is one of the effective quantitative metric. A higher value of EME suggests a better contrast. It approximates an average contrast in the image by dividing the image into non-overlapping blocks and finding a measure based on minimum mn_i and maximum intensity values mx_i in each block. Consider N blocks, for each block compute E_i as given in the following equation

$$E_i = 20 \times \log\left(\frac{mx_i}{mn_i}\right), \tag{6}$$

$$EME = \frac{1}{N}\sum_i^N E_i. \tag{7}$$

- The second measure used is *entropy* (H) [11,44]. The entropy of the enhanced images should not be lower than the entropy of the input image. Lower entropy conveys a loss of some image details. Higher values of entropy, means the image is rich in details. However, it also considers image noise as image details and thus sometimes give a higher value even for noisy images. The equation for discrete entropy measure is:

$$H = -\sum_i^K P_i \times \log_2 P_i, \tag{8}$$

whereP_i is the normalized histogram.

- AMBE [23] is a metric that measure the brightness preservation. A lower value of AMBE corresponds to a mean brightness of enhanced image closer to the original image. It is computed as follows:

$$AMBE = f(x, y)_{mean} - g(x, y)_{mean}, \tag{9}$$

where$f(x, y)_{mean}$ is the mean of original image $f(x, y)$ and $g(x, y)_{mean}$ is the mean of the contrast enhanced image $g(x, y)$

- Contrast enhancement leads to increased edge sharpness that can be measured using *Tenengrad criterion* (TEN) [33]. A higher value of TEN suggests sharper edges. This measure is based on gradient magnitude maximization computed from the gradient magnitude of an image $g(x, y)$. TEN is calculated as:

$$TEN = \sum g(x, y)\, if g_n(x, y) > TH, \tag{10}$$

where $g_n(x, y)$ is the normalized gradient magnitude and TH is the threshold value. We have tested using this measure using$TH = 0.5$.

- Structural and edge information is critical for the precise detection of landmarks in cephalometric images. The contrast enhancement algorithms should not dislocate or lose edges or modify the image texture. *Mean structural similarity index measure* (MSSIM) [24] helps us to measure how well has the image structures been preserved in the enhanced image. SSIM measure combines luminance, contrast, and structural comparisons. The SSIM index between the true image $I(x, y)$ and the enhanced image $G(x, y)$ are computed within a local window of size 11×11 and then the mean of all such local windows gives the MSSIM. MSSIM value is in the range of zero to one. Higher value suggests the better preservation of image structures.

$$MSSIM(I, G) = \sum_{j=1}^{M} \frac{\left(2\mu_{Ij}\mu_{Gj} + C_1\right)\left(2\sigma_{Ij,Gj} + C_2\right)}{\left(\mu_{Ij}^2 + \mu_{Gj}^2 + C_1\right)\left(\sigma_{Ij}^2 + \sigma_{Gj}^2 + C_2\right)}, \tag{11}$$

where μ_{Ij}, μ_{Gj}, σ_{Ij}^2 and σ_{Gj}^2 are the average gray values and variances in local windows in images $I(x, y)$and $G(x, y)$ respectively, $\sigma_{Ij,Gj}$ is the covariance of $I(x, y)$and $G(x, y)$, C_1 and C_2 are the variables to stabilize the division with low magnitude denominators. The variables are computed as $C_1 = (k_1L)^2$, $C_2 = (k_2L)^2$, where L is the dynamic range of pixel values in the whole image and $k_1$and k_2

are constants, which are fixed in the present analysis as $K_1 = 0.01$, and $K_2 = 0.03$⟨*REFNUMLINK*⟩[40]. Higher values of MSSIM represent better preservation of structural information.

- *Singular value decomposition measure* (SVD-M) [45] gives us the global error between the original image and the enhanced image regarding the distance between the singular values of the initial image block and the singular values of the enhanced image block. This measure helps us to find out if any distortions are added to the enhanced image. A value of zero suggests no distortions are added. The SVD-M is computed by using the following equations:

$$D_i = \sqrt{\sum_{i}^{n} \left(s_i - \hat{s}_i\right)^2}, \tag{12}$$

wheres_i is the singular values of the original image block, $\hat{s}_i$ is the singular values of the enhanced image block and n is the block size.

$$SVD_M = \frac{\sum_i^N |D_i - D_{mid}|}{n}, \tag{13}$$

where D_{mid} represents the mid point of the sorted $D_i s$ and N is the number of blocks.

- To measure the contrast improvement between skeletal structure and the background and also between soft-tissue and the background *contrast-to-noise* (CNR) measure [25] is used. This measure combines the contrast of the object and SNR. Higher value suggests a better contrast.

$$CNR = \frac{\mu_a - \mu_b}{\sigma_c}, \tag{14}$$

where μ_a the mean of *region of interest* (ROI) in the test image and μ_b is the mean of background surrounding the ROI. $\sigma_c$is the standard deviation outside ROI.

4.2. Subjective analysis

Figs. 1 and 2 show, the low contrast images and their corresponding enhanced images using various contrast enhancement methods. For digital cephalometric images, the proposed algorithm gives the best results (Fig. 1). The enhanced images are naturally looking with higher contrast and sharper edges. The visual results provided by the proposed algorithm are similar to CLAHE except that the noise content is better suppressed. The HE method enhances the noise and adds artifacts to the contrast enhanced image. Whereas GLG [33] sometimes leads to a washed-out appearance in many cephalometric images as is evident from Fig. 1. HMF [34] gives natural looking enhanced images without noise artifacts, but the contrast enhancement is lower than the CLAHE and the proposed algorithm. GLIH [35] enhances the contrast of bony structure in cephalograms, however, it lowers the contrast of soft tissue, and some information is lost in the enhanced image. The wavelet-based method WAV1 does not lead to much improvement in overall contrast of cephalograms. WAV2 gives significant improvement in contrast between soft tissue and background, but the improvement in contrast between bony structure and soft tissue is not significant. The results for scanned low-quality cephalograms are shown in Fig. 2. In these images, CLAHE gives the best contrast, but in many of the test images noise near the nose region is enhanced with improvement in contrast. The results provided by the proposed algorithm are similar to GLIH except that the proposed algorithm loses some information near the edges. The results of all other methods are similar to the digital cephalograms.

Fig. 3 shows the histograms of original and enhanced images given in Fig. 1. The histogram of the original test image has limited dynamic range and is not uniform. HE extends the dynamic range and improves the uniformity of the histogram. However, a significant number of peaks remain at the beginning of the gray scale range, which leads to noise amplification. There are wide gaps in the histogram showing isolated bins resulting from over quantization. Also, the shape of the histogram is not maintained. Information in the image may be changed. CLAHE extends the histogram to cover the entire gray scale range. The histogram is uniform with reduced peaks and without any gaps. GLG only extends the dynamic range of the histogram slightly. Instead of suppressing the peaks, it gives rise to higher peaks at the end of the histogram. HMF gives some improvement in dynamic range and uniformity while maintaining the shape of the histogram. GLIH covers the entire dynamic range, makes the histogram more uniform and reduces the peaks. However, its histogram has some isolated bins. In the case of the two wavelet based methods histogram of WAV1 shows the slight spread of the histogram and retains its shape, but the histogram is shifted towards the right. The WAV2 method gives a perfectly uniform histogram. The histogram of the proposed method retains the shape similar to the original image. It makes the histogram uniform, extends its dynamic range and significantly reduces the peaks. The intensity profile shown in Fig. 4 is a set of intensity values taken along a line segment at equally spaced locations from the image. The line segment is drawn from the foreground area in the image with a large number of edges. The intensity profile gives us information regarding the edge characteristics. The peaks and valleys correspond to the edge pixel locations. Fig. 4 shows that the intensity profiles of GLIH, CLAHE, and the proposed method are similar in shape to the profile of the original image. Also, the height of the peaks and depth of valleys are increased, suggesting that these three methods not only preserve the edges but also enhance them. Whereas all other methods show some deformation of intensity profile that confirms that the edges are not well preserved.

4.3. Quantitative analysis

Quantitative assessment is done using eight metrics as it is tough to measure the effectiveness of any contrast enhancement algorithm using a single metric as a benchmark.

Fig. 5 shows an average of EME, H, and AMBE values for the images enhanced by different methods. Improvement in contrast, leads to better visibility of the image details. Moreover, HE, GLIH, and WAV2 give the highest EME values, but due to very sharp increase in contrast, the images may give an unnatural look. CLAHE is one of the benchmark techniques for contrast enhancement. The proposed algorithm gives improved EME than CLAHE, GLG, and HMF methods, however the change in EME is not as high as HE and GLIH methods. Hence, the images enhanced by the proposed algorithm are natural looking with improved visibility of details. WAV2 gives the highest value of H. The proposed algorithm gives the second highest values of H that are slightly better than CLAHE. HMF and GLIH also offer some improvement in H as compared to the input image. In images enhanced by HE and GLG, there is loss of some image detail leading to decrease in H from the input image. The AMBE values of the proposed algorithm are either comparable or lower than CLAHE enhanced images. All the other methods give comparatively higher values of AMBE. Thus, the proposed algorithm best preserves the image brightness. The TEN values are given in Fig. 6. The value provided by the proposed method is close to the original image and better than most other methods. CLAHE gives comparatively high value, suggesting that noise is also enhanced along with the edges.

The MSSIM values are shown in Fig. 7. WAV2 gives the highest value of MSSIM. The proposed algorithm gives slightly lower value,

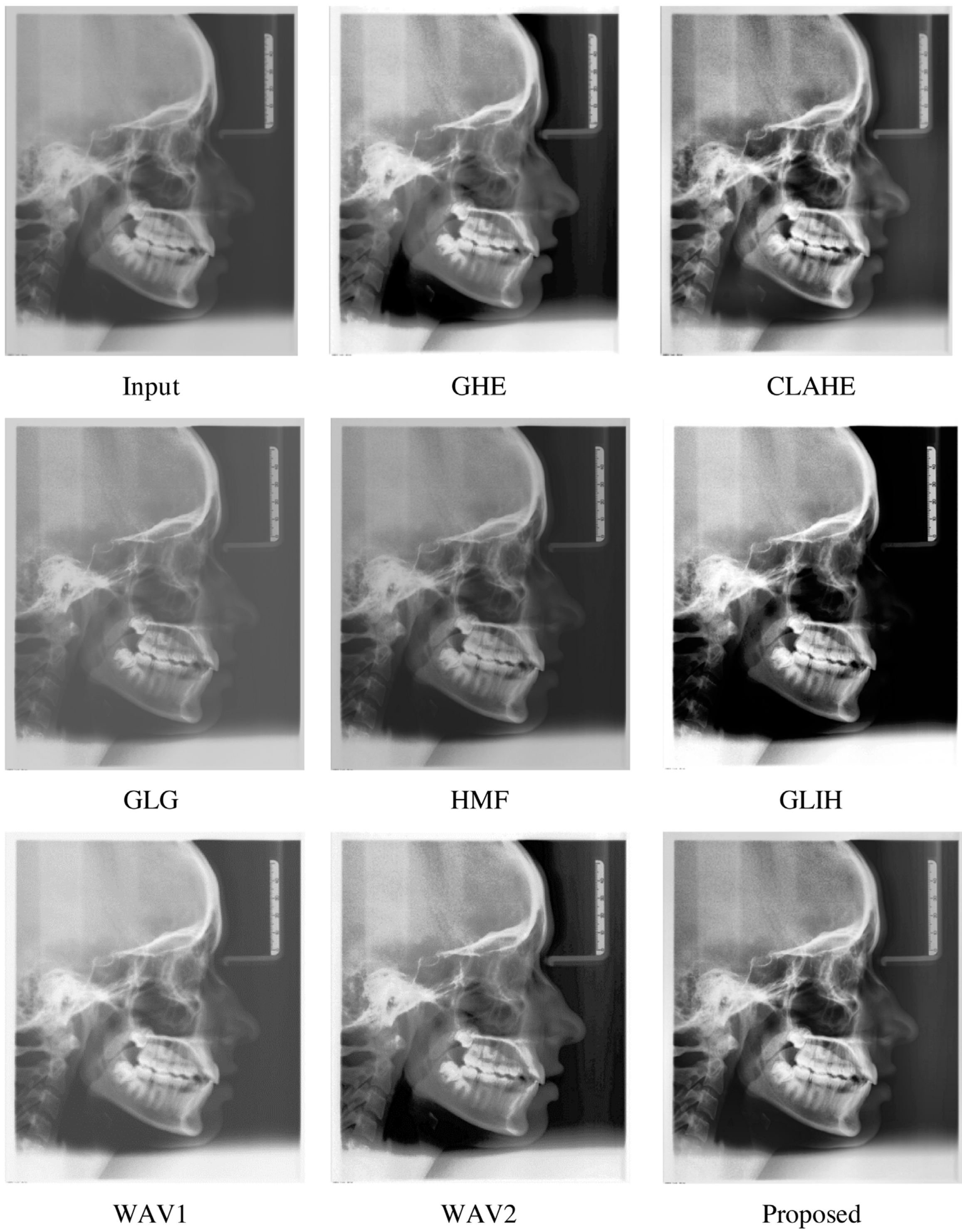

Fig. 1. Input low contrast digital cephalogram image and enhancement results.

but much better than the other methods. HE gives the lowest value of MSSIM.

The results of SVD-M are shown in Table 1. The proposed method gives the lowest value of SVD-M suggesting that it adds less distortion in the enhanced image. Fig. 8 demonstrates that the proposed method gives the best CNR.

For computing time complexity for each image, all the methods are run 10 times and the average is computed. Refer Fig. 9 for the quantitative values of the average CPU time for each method and Fig. 10 for the standard deviation of average CPU time. The proposed method is about 50% faster than both wavelet based methods. It is slower than the other four methods, but still it takes less than 0.5 s to enhance an image of size 544×456.

The proposed method is developed by combining CLAHE with a modified histogram equalization technique that uses edge pixels to compute the histogram (GLIH). However, our technique differs significantly from GLIH as discussed previously in Section 3.2. The proposed algorithm uses wavelets to extract gradient information in the image. The following are concluding remarks with respect to CLAHE and GLIH:

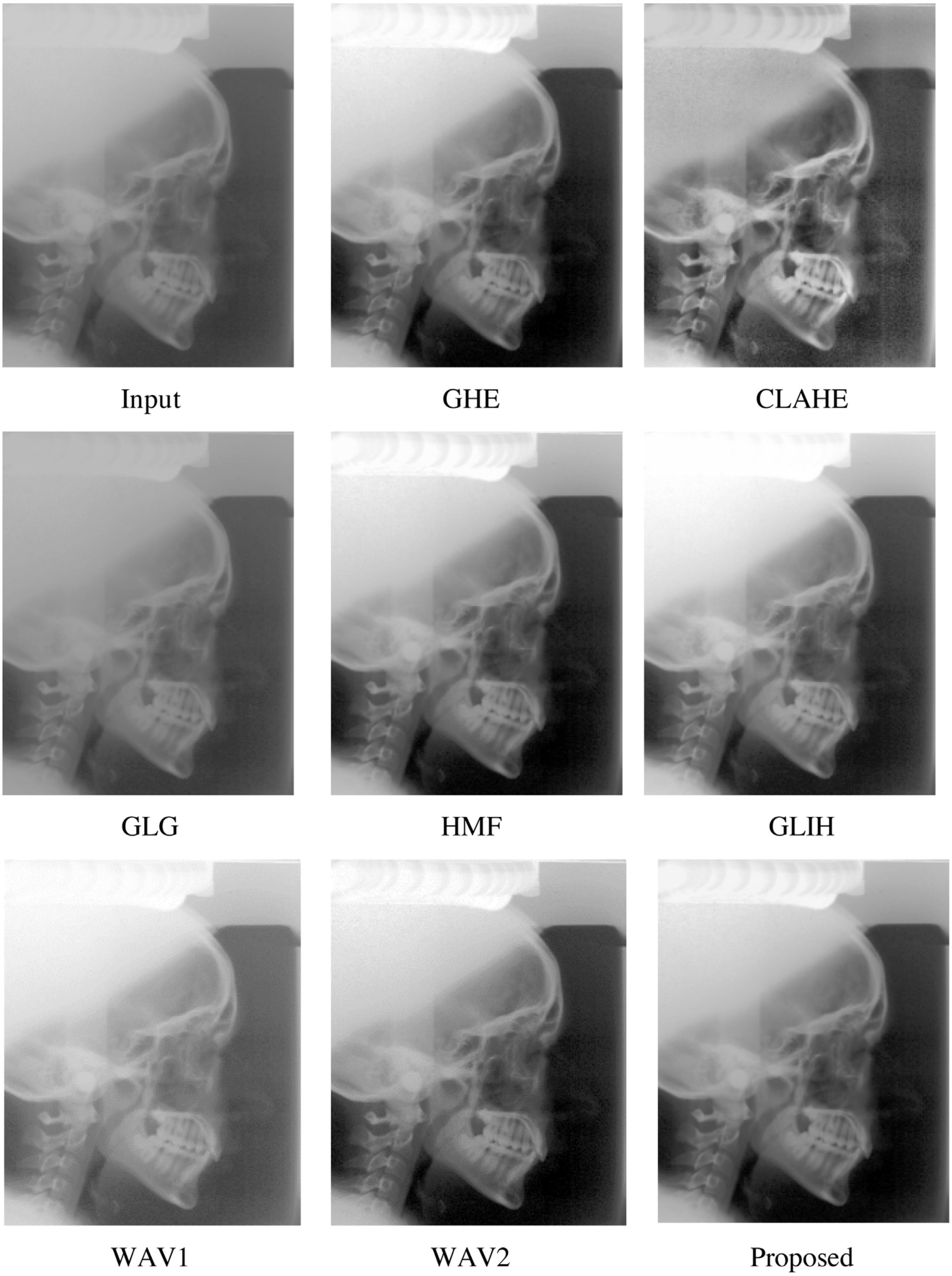

Fig. 2. Input low contrast scanned cephalogram image and enhancement results.

Table 1
Average value of SVD_M.

Method	HE	GLG	HMF	GLIH	CLAHE	WAV1	WAV2	Proposed
SVD_M	27.278	26.117	20.554	25.971	17.131	13.255	20.278	13.084

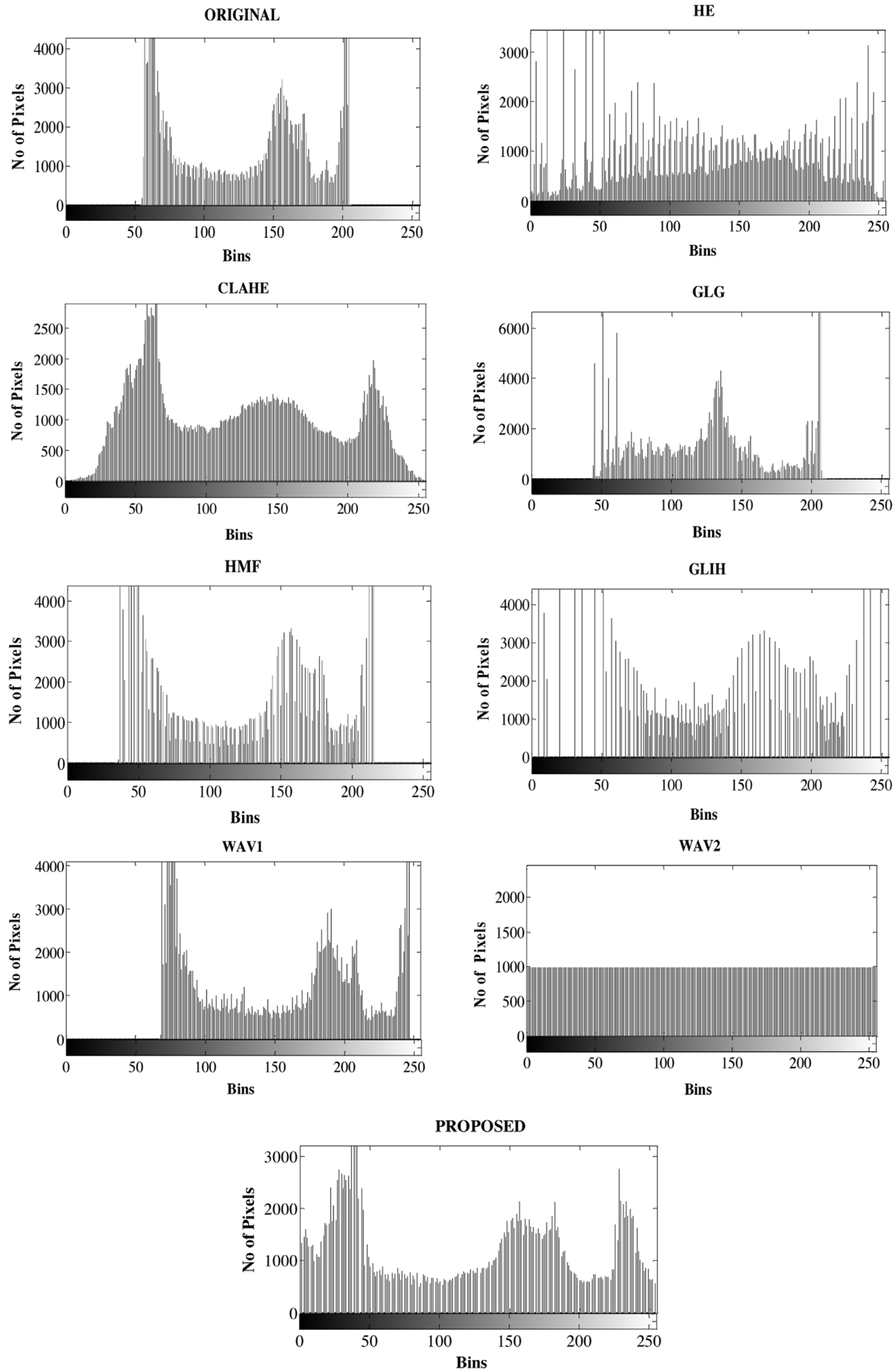

Fig. 3. Histograms of images given in Fig. 1(a) Input low contrast image and enhanced images.

- Both the proposed method and CLAHE extend the histogram to cover the entire gray scale range. The histogram is uniform with reduced peaks. GLIH covers the entire gray scale range, makes the histogram more uniform and reduces the peaks. There are wide gaps in the histogram showing isolated bins resulting from over quantization.
- It is evident from Fig. 4 that the intensity profile of GLIH, CLAHE, and the proposed method is similar in shape to the original image. All three methods preserve the image edges and enhance the edge sharpness.
- The results of seven quantitative measures are shown in Table 2.

From the above table, it is clear that CLAHE best preserves the image brightness, give the highest value for TEN that signifies max edge sharpness (sometimes this high value is due to the enhanced noise) and is the most time efficient. GLIH gives the highest average contrast (EME). The proposed method also preserves

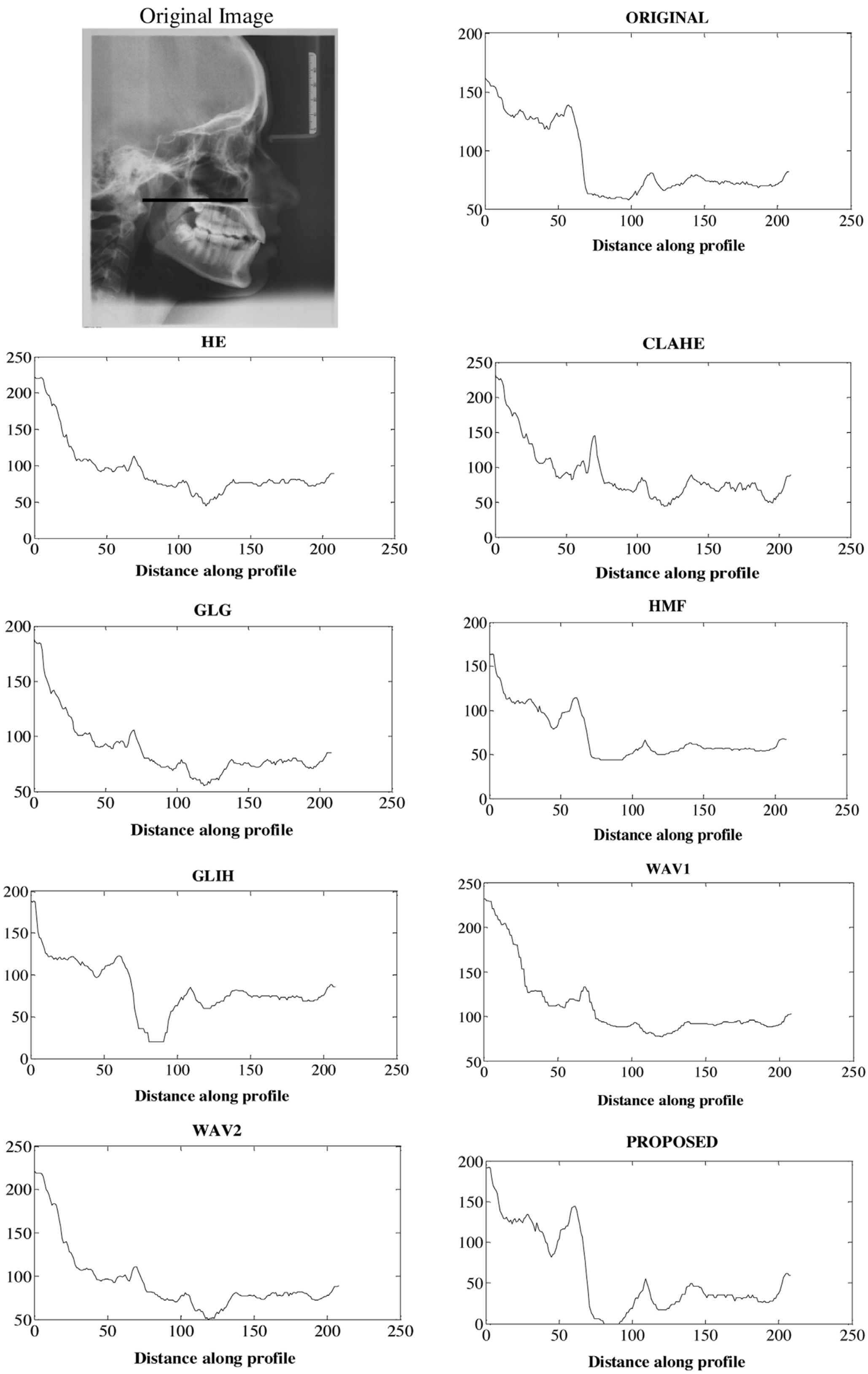

Fig. 4. Intensity profile of a line scan at a location shown in original image for original image and the image after being enhanced by different methods.

the image brightness (AMBE value close to CLAHE). The proposed method gives higher value of H and TEN than GLIH suggesting edge enhancement. It best preserves the image structures and does not add any distortions (highest value of MSIMM and lowest value of SVD-M). It also gives the maximum value of local contrast enhancement (highest CNR). However, the proposed method is slower than both CLAHE and GLIH.

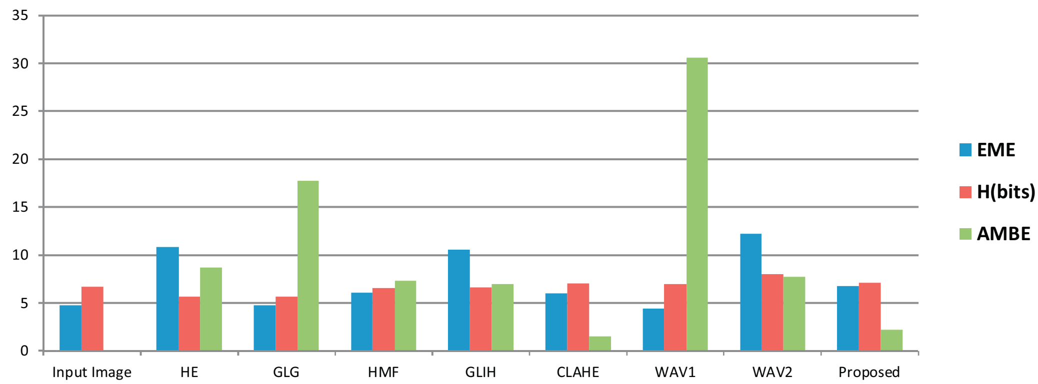

Fig. 5. Average values of EME, H, and AMBE.

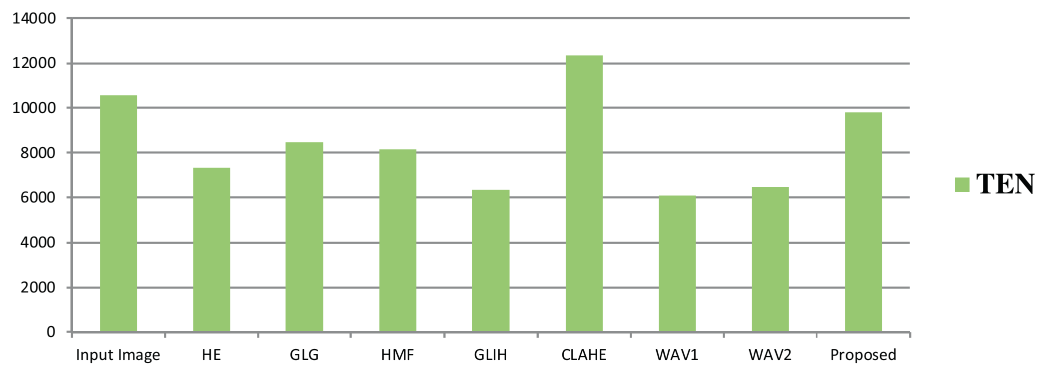

Fig. 6. Average value of TEN.

Fig. 7. Average value of MSSIM.

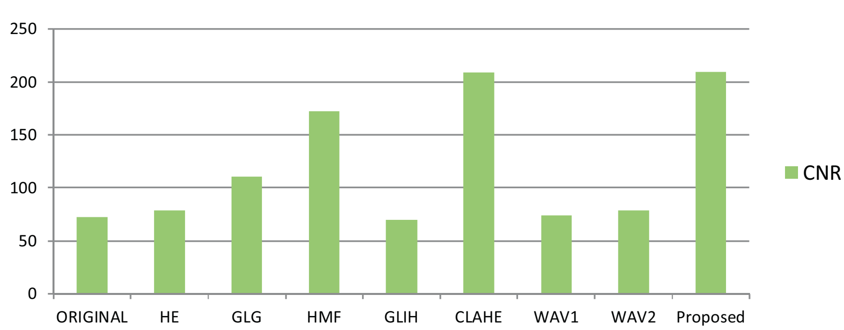

Fig. 8. CNR values for the images enhanced by different methods.

5. Summary

- The histogram of the images enhanced by the proposed method covers more dynamic range, is uniform with truncated peaks, and without wide gaps. All this shows that the proposed method is effective for contrast enhancement of cephalometric images.
- The proposed method gives the best contrast enhancement between skeletal structure and the background and also between

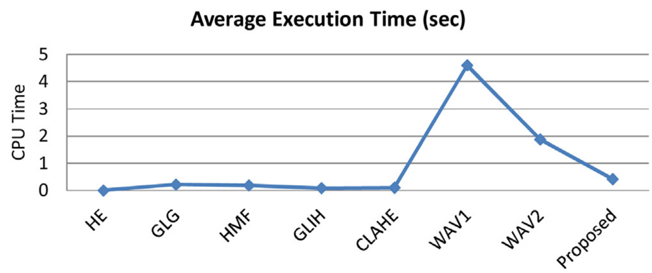

Fig. 9. Average execution time for different methods.

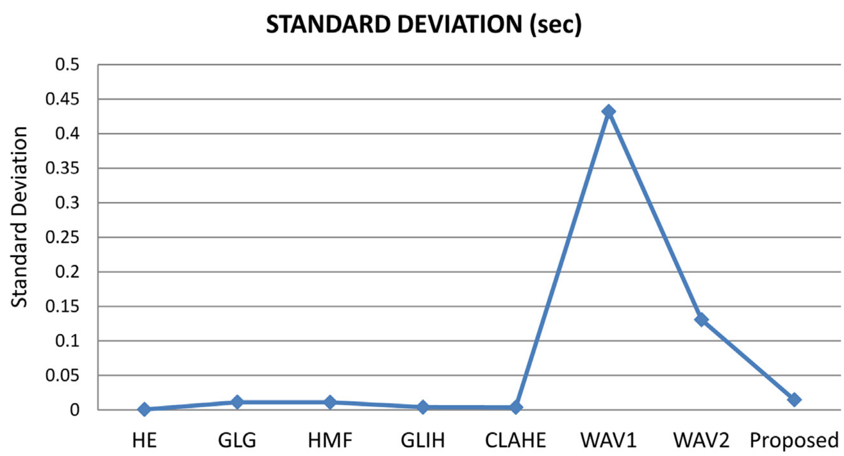

Fig. 10. Standard deviation of average execution time for various methods.

Table 2
Comparison of CLAHE, GLIH and the proposed method considering average values of the eight quantitative measures.

Method	Quantitative Measures							
	EME	H	AMBE	TEN	MSIMM	SVD-M	CNR	Time Complexity (sec)
CLAHE	5.9790	6.9840	**1.5289**	**12334**	0.9456	17.131	209.09	**0.1035**
GLIH	**10.6007**	6.6021	6.9390	6355	0.8321	25.971	69.65	0.2245
Proposed	6.7580	**7.0812**	2.2260	9795	**0.9818**	**13.084**	**209.65**	0.4287

The best value is highlighted in bold.

the soft tissue and background as is evident from the average value of CNR that is highest for the proposed technique (209.65) comparable to CLAHE (209.09). The average EME value is also improved from 4.7683 to 6.7581 corresponding to an improvement in average contrast. The value of EME is not as high as for the HE or WAV2. A very high value signifies excessively contrast enhancement leading to unnatural looking images.

- The proposed method conserves and enhances the edges. This is confirmed by the second largest value of average Entropy (7.0813) that is slightly lower than WAV2 (7.7191), and the second highest value of average TEN (10567.7) only lower than CLAHE (12334.9). The intensity profile (Fig. 4) also suggests that the proposed method not only preserve the edges, but also enhance them. Intensity profile changes when WAV2 is applied leading to a modification of edge information.
- The proposed method gives one of the highest values of average MSSIM (0.9818) comparable to WAV2 (0.9897), signifying that the image structure is well preserved. In the case of SVD-M, the proposed method gives the lowest average value (13.084), CLAHE gives second highest values of 17.131. WAV2 gives substantially higher value at 20.278 showing the addition of least distortion to the enhanced image.
- The brightness is well preserved with an AMBE value of 2.22 that is comparable to CLAHE with AMBE value of 1.53 and much lower than all other methods.
- The time complexity of five methods (HE, CLAHE, GLG, HMF, GLIH) is less than the proposed method, but still it takes less than 0.5 s to enhance an image of size 544 × 456. The time complexity of wavelet based methods is significantly higher.

6. Conclusions

In this work, we proposed an efficient contrast enhancement method for cephalometric images. The proposed method gives the best contrast enhancement between skeletal structure and the background and also between the soft tissue and background. The method gives minimum loss of structural information, changes in mean brightness of the image and the minimum addition of artifacts. The algorithm is well suited for contrast enhancement of cephalometric images.

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