Methods of Images Contrast Enhancement

https://github.com/mrugnivenko/Skoltech-NLA-MRI

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1 Problem statement

Image contrast enhancement is considered as the most useful technique permitting a better appearance of the low contrast images. It is especially important in Brain Magnetic Resonance Imaging (MRI), which is helpful and secure medical imaging technique permitting efficient brain diagnosis and exploration by discovering brain maturity and abnormalities. These images are usually affected by noise, artefacts, speckles and poor quality. Low contrast, as well, is one of the main problems that disturb the production of medical images.

The formal problem statement is following: use different approaches to transform the low contrast image (A - 2-dimensional array with size 256×256. a_{ij} - color value of pixel (i, j), $a_{ij} \in [0, 255]$, where 0 is black and 255 is white.) to the image of the same size, but with better contrast, and compare the results, using different quality metrics to find out, which approach performs better in witch sense.

In our research we've used 6 following metrics: PSNR, QRCM, SSIM, FSIM, AMBE, EME. They are responsible for different aspects of enhancement process: noise reduction, relative change of contrast, structure similarity, feature similarity of raw and transformed image, but still we want our enhancement process to optimise them all.

So we are looking for

$$\min_F Q(F(x), x),$$

where x is low contrast image, F is enhancement transformation, Q is aforementioned quality metrics.

2 Ideas and mathematical description of the algorithms

2.1 Histogram Equalization methods

The objective of the Histogram Equalization (HE) techniques is to give a linear trend to the cumulative probability function associated to the image.

The cdf is a cumulative sum of all the probabilities lying in its domain and defined by:

$$cdf(x) = \sum_{k=0}^{x} p_k$$

$$p_k = \frac{number\ of\ pixels\ with\ intensity\ k}{total\ number\ of\ pixels}$$

$$k = 0, 1, \dots, 255$$

So the following formula is used to get the transformation for each pixel intensity i:

$$T(i) = 255 \cdot cdf(i)$$

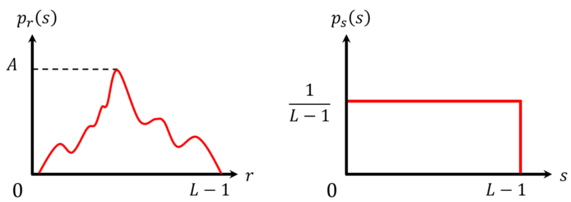

Figure 1: Histogram equalisation example. $p_r(s)$ is equal to p_k for initial image and $p_s(s)$ to p_k for transformed. r and s are color intensities of initial and transformed image respectively, L is total number of different pixel intensities (256 in our case).

Adaptive Histogram Equalization differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image.

2.2 Contrast Stretching

Contrast stretching or normalization is a simple image enhancement technique that attempts to improve the contrast in an image by 'stretching' the range of intensity values it contains to span a desired range of values. It differs from histogram equalization in that it can only apply a linear scaling function to the image pixel values. As a result the enhancement is usually less harsh.

Before the stretching can be performed it is necessary to specify the upper and lower pixel value limits over which the image is to be normalized. Often these limits will just be the minimum and maximum pixel values (0 and 255). Call the lower and the upper limits a and b respectively.

Algorithm scans the image to find the lowest and highest pixel values currently present in the image. Call these c and d. Then each pixel color i is scaled using the following function:

$$T(i) = (i - c) \cdot \frac{b - a}{d - c} + a$$

The problem with this is that a single outlying pixel with either a very high or very low value can severely affect the value of c or d and this could lead to very unrepresentative scaling. Therefore a more robust approach is to first take a histogram of the image, and then select c and d at the 5th and 95th percentile in the histogram. This prevents outliers affecting the scaling so much.

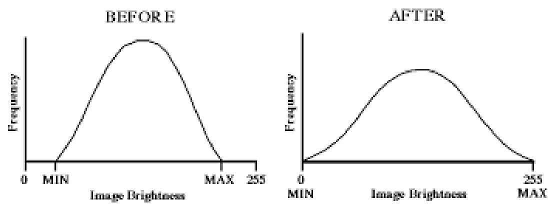

Figure 2: Contrast Stretching example

2.3 Singular value decomposition

Singular Value Decomposition (SVD) is if not the most important, than the most applied technique in the numerical linear algebra. The key point of the SVD is that any matrix $A \in \mathbf{C}^{n \times m}$ can be represented as the product of three matrices:

$$A = U \cdot \Sigma \cdot V^*$$

Where U, V are unitary and Σ is diagonal with singular values of A on the diagonal. Along with other applications, SVD can be useful for contrast enhancement. There are methods, like (1), for this task, based on updating the singular value matrix, which contains intensity information of the input image, on the low sub-band input image. In these recent works, SVD was used to obtain the ratio of highest singular value of the created equalized matrix, generated by HE, over a normalized input image.

2.4 Discrete wavelet transform

Discrete wavelet transform (DWT) is a technique for analysis, de-noising and compression of signals and images, which has recently become quite popular. The goal of using the DWT in an algorithm of filtering and compression biomedical signals is the possibility of choosing the signal's coefficients with a significant energy and discards the others that have a very low percentage of all energy. This is possible because in every level of decomposition, the energy of different frequencies and time position is related to a specific coefficient. The most commonly used set of discrete wavelet transforms have Daubechie wavelet functions under the hood. This methods are based on the use of recurrence relations to generate progressively finer discrete samplings of an implicit mother wavelet function; each resolution is twice that of the previous scale.

2.5 Linear algebra based methods

In medical images histogram based methods suffers from pixels gray levels concentration. Therefore, SVD can overcome this problem. Hence, we consider low contrast T1-w brain MRI as input images denoted as (A1) on which we apply the GHE method to have equalized images referred as (A2). By using the DWT for the original (A1) and the processed equalized images (A2), we obtain four frequency sub-bands labelled as (LL1), (LH1), (HL1), (HH1) and (LL2), (LH2), (HL2), (HH2) respectively as it is shown in Fig.3. SVD would be applied on the (LL1) and (LL2) of the original and the equalized images respectively. The reason behind using (LL) sub-band was in fact to protect edge information presented in the high frequencies and modify the in tensity information concentrated in low frequency.

SVD decomposition lead to the following matrix factorization:

$$LLi = U_{LLi} \Sigma_{LLi} V_{LLi}^*$$

In order to equalize intensity information of the image, correction coefficient ξ is introduced. Usually the new singular matrix Σ is calculated by multiplying the singular matrix of the equalized sub-band image Σ_{LL2} by correction coefficient ξ.

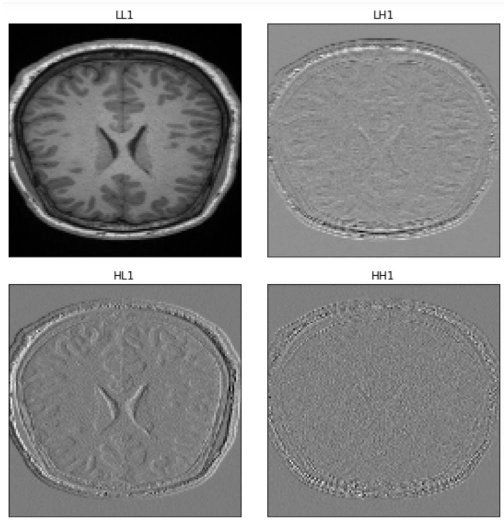

Figure 3: Image DWT decomposition for A1

There are different methods to calculate the correction coefficient ξ in order to estimate the singular value matrix:

In 2015, Randa Atta (4)

$$\xi = \frac{\max(\Sigma_{LL2})}{\max(\Sigma_{LL1})}$$

In 2014, Bhandari (5)

$$\xi = \frac{\max(U_{LL2})}{\max(U_{LL1})}$$

In 2016, Bhandari (3)

$$\xi = \frac{\max(U_{LL2}) + \max(V_{LL2})}{\max(U_{LL1}) + \max(V_{LL1})}$$

Also there are different methods to calculate new singular matrix Σ:

In 2014, Bhandari (5)

$$\Sigma = \xi \cdot \Sigma_{LL2}$$

In 2016, Bhandari (3)

$$\Sigma = \xi \cdot \Sigma_{LL2}$$

In 2015, Randa Atta (4)

$$\Sigma = 0.5 \cdot (\xi \cdot \Sigma_{LL1} + \frac{1}{\xi} \cdot \Sigma_{LL2})$$

However, method introduced by Randa Atta (4) cannot be applicable for all types of input image. To overcome this limitation, M. Sahnoun (7) propose the following adjustable method to find new Σ:

$$\Sigma = \mu \cdot \xi \cdot \Sigma_{LL1} + (1 - \mu) \cdot \frac{1}{\xi} \cdot \Sigma_{LL2}$$

The purpose of a parametr μ is to adjust the contrast of input images with a greater flexibility. The next step is to reconstruct the new LL sub-band image using ISVD:

$$LL = U_{LL2} \Sigma V_{LL2}^{*}$$

And the final step is computing the resultant enhanced image using IDWT.

Therefore, the workflow is the following:

Step 1: A low contrast T1-w MRI image has been selected.

Step 2: Equalizing T1-w MRI image (A1) using GHE technique in order to generate equalized image (A2).

Step 3: After equalization, computing DWT decomposition of both original image (A1) and equalized image (A2) in order to divide each image into four frequency sub-band images which are (LL1), (LH1), (HL1), (HH1) and (LL2), (LH2), (HL2), (HH2) respectively.

Step 4: After getting DWT frequency sub-band images, SVD is applied on both low frequency components (LL1) and (LL2) leading to threematrix factorization U, V and Σ.

Step 5: Ccalculating the correction factor ξ.

Step 6: Estimating the new Σ

Step 7: Applying Inverse SVD to generate new LL.

Step 8: Finally, applying Inverse DWT to obtain enhanced resultant T1-w MRI image.

Since algorithm proposed by M. Sahnoun (7) is the newest one, we will mostly compare its performance with performances of other algorithms. So, here and further we will call this method the considered method.

3 Experiments description and results

In these experiments, we used low contrast T1-w MR brain images for the contrast enhancement process. The considered method was implemented in a Python environment and during the entire simulation process, we have considered 256×256 as pixel resolutions. As for the DWT process, the performance of two wavelet functions: $9/7$ tap Daubechie and 1 tap Daubechie. The last was showed to be more efficient. The efficiency of considered method was compared with 3 recent state of the art methods detailed above. The enhanced images using different contrast enhancement methods are shown in Figure 4. Histogram graphs accompanies each original and enhanced images.

Our input image is considered as low contrast image because its histogram plot has limited dynamic range as it is shown in Figure 4.

Considered method has provided slightly better contrast and details for human visual perception than the rest of methods under the influence of the histogram graph which has occupied all gray values intensities. As a consequence, considered contrast enhancement method have shown better distinction between brain tissues and have preserved all (WM), (GM) and (CSF) pixel edges. Thus, the success of the considered method was in fact due to the use of an adjustable μ parameter with a weighted sum of the input and the equalized singular value matrix.

3.1 Quantitative analysis

In order to support the qualitative analysis presented in the last section, a quantitative analysis is therefore important. For this purpose, different metrics like PSNR, QRCM, SSIM, FSIM, AMBE and EME are considered. All T1-w brain low contrast MR images are processed with the previously discussed methods and the values for indicated quantitative metrics are computed and illustrated in Figure 5.

• Measure of Peak Signal-to-Noise Ratio (PSNR) measures the ratio between the maximum possible value of a signal and the power of distorting noise that affects the quality of its representation.

• Measure of Quality-aware Relative Contrast Measure (QRCM) gives idea about contrast measure and image quality together. QRCM penalizes the contrast changes when there is a significant difference between the gradients of original and enhanced images. This is happened generally when there are visual distortions on the processed image. Thus, QRCM does not only measure the relative change of contrast but also takes the distortion introduced on the enhanced image relative to the considered original image. Negative QRCM values indicate that considered contrast enhancement algorithm distorted enhanced image as comparing to the original one.

• Structure similarity index measurement (SSIM) is a metric based on measuring the similarity between two images. The SSIM can take values in range. Higher value suggests the better preservation of image structures.

• Feature similarity index measurement (FSIM) guides us to determine how well has the image feature been preserved. Higher value suggests the better preservation of image features.

• Absolute Mean Brightness Error (AMBE) presents the degree of brightness preservation between mean of input and enhanced images. Better brightness preservation is concluded for a lower AMBE value.

• Measure of enhancement by entropy (EME) is used to evaluate the quality of contrast enhancement. A higher value of EME suggests a better contrast.

Histogram Equalisation method, Adaptive Histogram equalisation and Contrast stretching in some metrics show the best and in some metrics show the worst results. Thus the are not really universal and have their own significant disadvantages. The other 3 methods, including the considered one, show more stable results in all 6 metrics. Varying μ coefficient we can slightly change characteristics of enhanced method, depending on what we need. However there is no coefficient, which performs best in all metrics.

3.2 Time analysis

We examined how different methods of image contrast enhancement differ from each other using quantitative metrics, but it is also important to check whether or not considered method is suitable for online use, to enhance the quality of not only images, but videos.

The analytical complexity of histogram based methods and contrast stretching algorithm are based on image dimension size n and equal to $O(n^2)$. Considered method uses SVD decomposition, therefor complexity of it is $O(n^3)$ and therefor it can process less number of images in a given amount of time. However, numerical experiment shows, that for image size 256×256 the amount of images processed in 1 minute with proposed method is 32 which is enough to conclude, that this method is suitable for real-time video enhancement.

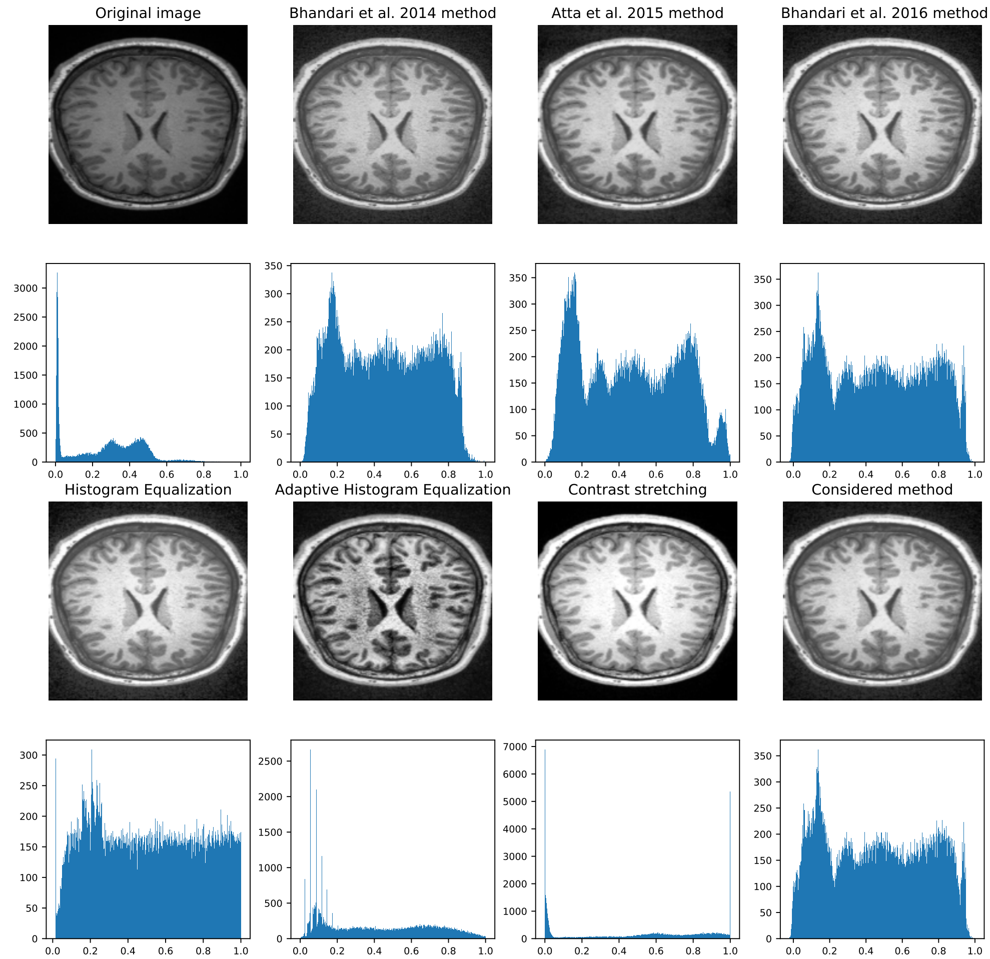

Figure 4: Visual qualities of original and enhanced images using various enhancement methods and histograms of pixel intensities of corresponding enhanced images.

Conclusion

During the work on this project, the latest method (7) of image enhancement was compared with older SVD based techniques and with alternative methods. The experiments have shown that SVD based methods are more universal and show great performance on average. Also, the considered method has the best quality among all methods and, moreover, it is way more flexible, because one can manually select the correction parameter μ for every particular image. In addition, the time of the algorithm execution was measured, and it was shown that the considered technique is suitable for online image enhancement.

Acknowledgments

We acknowledge ADASE group and science-practical center n.a. Pirogov for data. All code for experiments is publicly available.[1]

[1] https://github.com/mrugnivenko/Skoltech-NLA-MRI

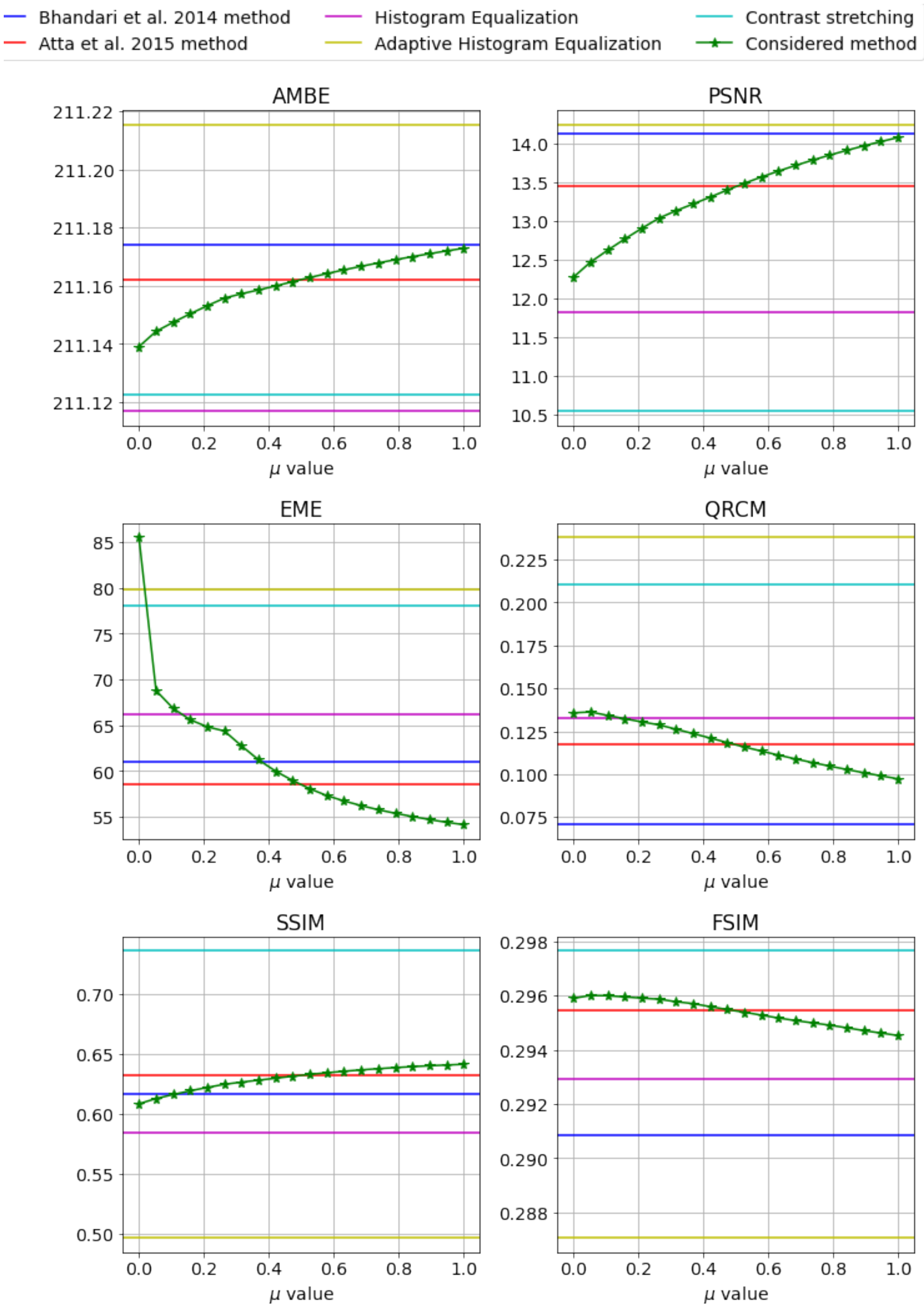

Figure 5: Representation of PSNR, QRCM, SSIM, FSIM, AMBE and EME values for the (Bhandari, et al., 2014) method, (Atta et al., 2015) method, Histogram equalisation method, Adaptive Histogram equalisation method, Contrast stretching method and Considered method.

Distribution of the work

Vitaly Ugnivenko - image preprocessing, realization and description of proposed method, report writing, making presentation.

Liliya Lemikhova - realization of metrics for quantitative results, description of results, report writing, making presentation.

Nikita Kubrakov - realization of alternative methods for images contrast enhancement, time analysis, report writing, making presentation.

Mikhail Kuimov - realization of 9/7 DWT and experiments with it, realization of alternative methods for images contrast enhancement, report writing, making presentation.

References

[1] *A.Kumar - Improved normalised difference vegetation index method based on discrete cosine transform and singular value decomposition for satellite image processing.* https://digital-library.theiet.org/content/journals/10.1049/iet-spr.2011.0298

[2] *Y.Yang - Medical image enhancement algorithm based on wavelet transform.* https://digital-library.theiet.org/content/journals/10.1049/el.2010.2063

[3] *A.K.Bhandari and Anil Kumar - Dark satellite image enhancement using knee transfer function and gamma correction based on DWT–SVD.* https://link.springer.com/article/10.1007/s11045-014-0310-7

[4] *Randa Atta - Brightness preserving based on singular value decomposition for image contrast enhancement.* https://www.sciencedirect.com/science/article/abs/pii/S0030402615000625

[5] *A.K.Bhandari - Artificial Bee Colony-based satellite image contrast and brightness enhancement technique using DWT-SVD.* https://www.tandfonline.com/doi/full/10.1080/01431161.2013.876518

[6] *Tae Keun Kim - Contrast enhancement system using spatially adaptive histogram equalization with temporal filtering.* https://ieeexplore.ieee.org/abstract/document/663733

[7] *M.Sahnoun - A Modified DWT-SVD Algorithm for T1-w Brain MR Images Contrast Enhancement.* https://www.sciencedirect.com/science/article/abs/pii/S1959031819301290