Hybrid Cost Function for Medical Image Enhancement with Optimization Algorithms

Raghavarao Siripalli[1], Shailesh Deshmukh[2]

[1]Research Scholar, Kalinga University
[2]Professor, Kalinga University

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ABSTRACT
Medical image enhancement plays a critical role in improving diagnostic accuracy and treatment planning by enhancing the visibility of key anatomical structures and pathologies. In optimization-based enhancement techniques, the cost function is a pivotal component, guiding the enhancement process by quantitatively evaluating image quality. This paper explores the design and application of cost functions specifically tailored for medical image enhancement. We focus on optimizing key factors such as contrast, sharpness, signal-to-noise ratio (SNR), and edge preservation, which are vital for enhancing medical images while maintaining diagnostic integrity. Various optimization techniques, including gradient-based methods, genetic algorithms, and deep learning approaches, are applied to minimize the cost function. The impact of domain-specific constraints, such as preserving tissue texture and avoiding artificial artifacts, is also discussed. Experimental results on modalities such as MRI, CT, and ultrasound show that well-designed cost functions lead to significant improvements in image quality, thus facilitating better clinical outcomes and aiding medical professionals in accurate diagnosis.

Keywords: Medical images, Magnetic resonance imaging, Image Enhancement, Optimization, Image diagnosis.

1. INTRODUCTION

Image processing and image enhancement techniques are widely used in medical imaging, especially magnetic resonance imaging. A test called magnetic resonance imaging uses radio pulses and an attracting field to create images of the body, particularly the brain or cerebrum. In essence, the MRI imaging method is utilised in the medical field to produce incredibly high-quality pictures of the various human body parts. To diagnose brain tumours, spinal infections, various illnesses, shoulder injuries, bone tumours, and strokes, among other things the MRI is used. These MRI images visibly show which tissues are injured, and these MRI images are saved on a computer to help with future preparation and assistance. Sometimes, a contrast agent is added in order to improve the clarity of the MRI images. This agent helps identify blood clots, tumours, and inflammatory tissue regions. The specialists are provided with various upgraded image results so they can make an exact diagnostic and provide accurate outcomes.

Numerous factors could be involved because the medical images are processed at different phases of acquisition. It is essential to pre-process medical photos in order to improve their aesthetic appeal. Pre-processing of the medical images is used to improve specific qualities to remove noises and artefacts and also to raise the effectiveness of cancer detection. Following that are the steps of segmentation, feature extraction, and classification.

Enhancing the MR image quality and preparing it for subsequent processing by a machine vision system or human is the main goal of pre-processing. Furthermore, pre-processing offers the extras needed to enhance specific MR image properties. It enhances the signal-to-noise ratio, smoothes the inner portion of the region, eliminates unwanted background elements, and preserves the region's edges. Improving the signal-to-noise ratio and raw MR picture clarity are the two main goals of this research endeavour. The goal of the study project has been achieved by using a Histogram Equalisation based on the Hippopotamus Optimisation Algorithm. The raw medical image quality is improved and noise is reduced by applying the spatial domain approach. The morphological erosion operator, which is used to the input image to enhance the object outlines, is the optimum choice in the spatial domain. The erosion operator is applied using a radial structural element because the suggested contrast enhancement technique is meant for brain imaging, where most of the regions and borders have curved shapes. Furthermore, a comparison is made between the suggested method's performance and alternative approaches. While segmentation plays an important role in brain tumour identification, the quality of the raw MR images ultimately determines the outcome. Thus, attempts have been made to better the overall experience of brain tumour identification by the use of MR image pre-processing. The use of the tactics discussed in this chapter is justified by the following.

1. To enhance the raw MRI image quality and overall visualisation
2. To see high-quality outcomes and enhanced segmentation performance for brain tumour identification through enhanced raw MRI image quality.

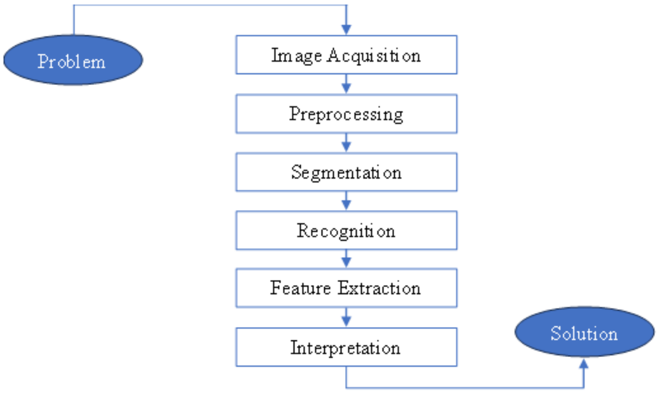
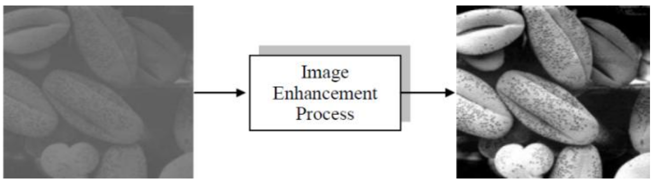


Figure 1. General procedure of image processing

One of the easiest and most interesting applications of digital image processing is image enhancement. Basically, the purpose of enhancement techniques is to either highlight specific interesting characteristics in an image or bring out details that are hidden. For example, altering contrast and brightness, etc.

Figure 2 (a). Process of the Image Enhancement technique



(i) Original input image **(ii) Enhanced output image**

Figure 2 (b). Image enhancement of low contrast image

2. LITERATURE SURVEY

Additional strategies for enhancing the quality of both general-purpose and medical photographs are presented in this section. Since the HE approach entirely alters the image's brightness, it is unable to produce photographs with improved lighting. As a result, an enhancement technique was created by performing HE independently on each of the two equal area sub-images that were created from the original image [6]. Lastly, merge the two sub-images to create a newly improved image. The author has demonstrated the algorithm's superiority in terms of information contents and brightness preservation. Once more, Soong-Der Chen et al. [7] introduced an approach called minimum mean brightness error Bi-histogram equalization, which is an extended version of BBHE, to maximize brightness preservation. According to a threshold value, the author of this study divides the image into two sub-images, which produce a lower Absolute Mean Brightness Error (AMBE).

In order to enhance and expand the brightness of the image, the author of this study [8] suggested a BBHE approach generalization. In BBHE, a picture is separated just once using the image's mean. However, the image separation in this article is done recursively and according to the corresponding mean. At recursion level r = 0, this algorithm is equal to HE; at recursion level r = 1, it is comparable to BBHE. In this work, recursion level r = 2 is used to provide greater brightness preservation and prevent undesired artifacts. Another strategy has been provided in [9] to maintain greater brightness, in which the procedure DSIHE conducted recursively. This technique is identical to the technique provided in [9] and the separation of

picture is conducted recursively based on respective median rather than mean. Recursion level assumed to be r = 2. After conducting imge division, process of HE is performed to each portion and lastly enhanced image is generated by integrating all the equalized sub-image.
However, the previously stated methods do not explain how to enhance low exposure images. These algorithms don't employ any parameters to regulate the rate of augmentation. So, for the quality improvement of low light photos, a technique is provided in [10] which is based on exposure threshold. In this paper, the augmentation rate is controlled by a clipping threshold. This technique maintains the information contents, controls the enhancement rate, and improves the visibility of low-exposure images. A new method for improving low light and night vision photos was proposed by the author [11] in 2014. It partitions the image recursively based on exposure threshold and uses HE in each partition. For low exposure photos, a different method of image enhancement [12] has been proposed, in which the input histogram is trimmed using the intensity median. The resulting histogram is then divided into four sub-images using individual means after being bisected with the aid of median intensity. Next, HE is carried out for every sub-histogram. This research uses performance metrics such as entropy, average luminance, background gray level (BGL), and AMBE to assess the algorithm's effectiveness.
The authors of this paper [13] proposed the HE background brightness preservation method to improve image contrast and preserve background brightness. This method splits the input image into a background layer and a non-background layer. Each subcomponent then undergoes an alignment process separately, and finally the two are combined to form an enhanced image. This method increases background levels above the original range, so the excess gain must be removed. Another sub-image containing lower gray levels will be extended to a larger range, so the output image can be properly corrected. In 2018, Zhao Wei [14] introduced a new approach to minimize entropy reduction and realize the Global HE method in two steps. They are the pixel population fusion (PPM) step and the gray level distribution (GLD) step. At the PPM stage, the population of the adjacent gray scale displayed with the same gray scale is combined in the entry histogram. At the GLD stage, the redistribution of the gray scale occurred on a combined histogram using the function of distribution of magazines, which controls the speed of improvement.
Although many HE-based algorithms have been proposed in recent years, few methods can provide natural enhancement across the entire luminance range. Therefore, to ensure natural enhancement, avoid over-enhancement, and avoid excessive smoothing, several methods have been presented in [15-16]. These methods are based on histogram partitioning, clipping, and HE techniques. These techniques can achieve several objectives, such as enhancing information content, controlling the enhancement rate, preserving brightness, and natural enhancement. Zohair et al. [17] proposed a method to improve the illumination of night-time images. The main goal of this algorithm is to preserve luminance in bright areas and increase luminance in dimly lit areas. For this, the author used logarithmic and exponential functions to improve and preserve brightness. Then, all the sub-images are integrated using the adaptive logarithmic image processing (LIP) technique. Finally, a modified S-curve is implemented to improve the image brightness. Paul et al. [18] introduced a plateau boundary based enhancement technique, where the segmentation of the clipped histogram is performed based on the standard deviation (SD).

3. PROPOSED METHODOLOGY

Image enhancement is one of the important image processing techniques to improve the quality of an image. It is also necessary to make the image good enough for further processing and interpretation. This is used as a preliminary treatment for various medical visualization systems, such as computer fault shooting (CT), X -rays, magnetic resonance imaging (MRI), and mammography. In general, medical images have very low contrast and contrast. Medical images are inherently highly complex due to the presence of multiple overlapping objects, which are subject to artifacts and geometric distortions. Therefore, artifacts must be avoided for a better diagnosis: objects or regions of interest (ROIs) may not be visible in low-contrast images [2]. Therefore, it is very difficult to understand such images [3], which paralyzes the diagnostic process and leads to incorrect measurements during diagnosis [4]. Therefore, image enhancement techniques are used to improve the visual quality of medical images and are very useful when segmenting tissues, diagnosing diseases, identifying fractures, detecting tumors and bleeding [5].
Histogram equalization (HE) [6] is one of the traditionally used methods to improve image contrast by changing the dynamic range scale and histogram distribution of the image. However, histogram equalized images exhibit annoying artifacts and increased noise. The overall brightness of the image is also significantly changed by this method. To preserve the brightness and improve the contrast of images, various enhancement methods have been developed, such as brightness-preserving bi-histogram equalization (BBHE) [7], dualistic sub-image histogram equalization (DSIHE) [8], and minimum mean brightness error bi-histogram equalization (MMBEBHE) [9]. However, the methods described above do

not explain the mechanism of controlling the enhancement rate [10, 11]. In [10], the author presented a new technique for enhancing low-light images called recursively separated exposure-based sub-image histogram equalization (RS-ESIHE). In image processing applications, enhancing images that contain weak edges is a challenging task. Therefore, the authors [12] proposed an image enhancement approach using intuitive fuzzy sets.
The flow/Block diagram of the proposed method is shown in the figure 3. This includes the following steps.
Step-1: The input image histogram is calculated.
Step 2: Determine the optimal threshold value to convert a grayscale image to a binary image using Otsu thresholding.
Step 3: The E_T (exposure threshold) of the original histogram is calculated to divide the histogram into two subhistograms. The sub-histograms represent the low and high exposure parts of the image.
Step 4: Next, each sub-histogram is split into two sub-histograms using optimal threshold parameters E_{tlow} and E_{tup}.
Step 5: The PDF of each sub-histogram is calculated and changed using the PDF value, which is the current amount of PDF value.
Step 6: The cumulative density (CDF) function of each sub-histogram is calculated using a modified PDF. The display function of each sub-histogram is then calculated using the CDF of each sub-histogram.
Step 7: Perform subregion histogram equalization.
Step 8: Normalization is performed to avoid artifacts.
Step 9: Image merging is performed to get the enhanced image.
Step 10: Estimate the fitness value using the proposed cost function.
Step 11: Find the optimal threshold and fusion rate using Hippo algorithm by minimizing the cost function.

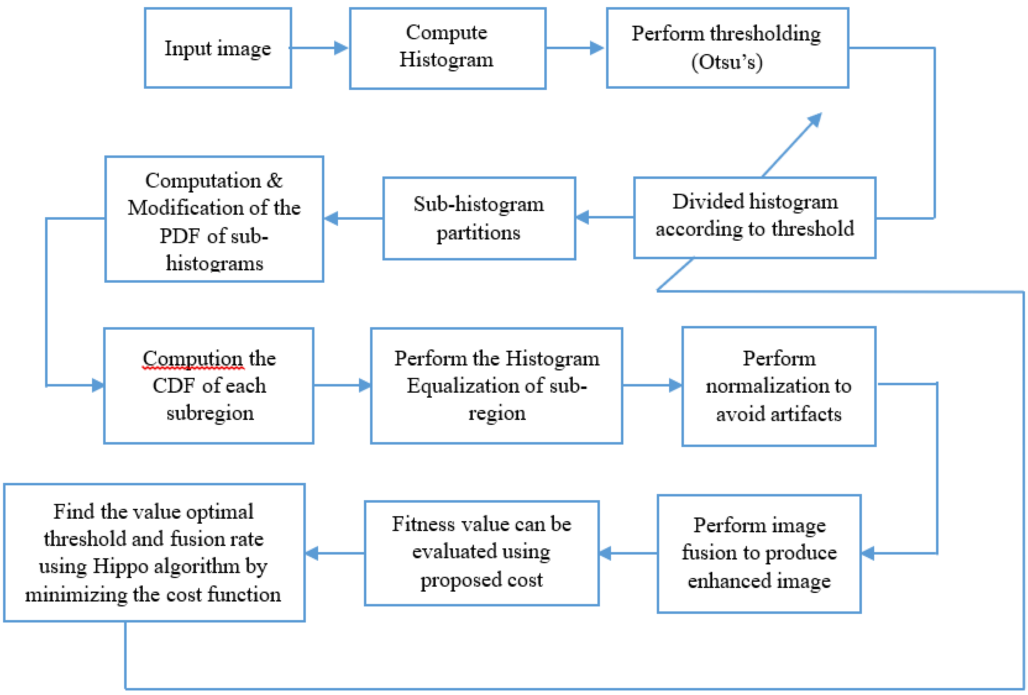


Fig 3: Proposed Image Enhancement Technique flowchart

Clipping threshold calculation

The histogram is clipped by computing the clipping threshold (Cavg). The primary goal of histogram clipping is to regulate the enhancement rate and prevent over-enhancing. By calculating the average of the mean and median image intensity levels, this clipping threshold is determined.

C_{median}= median(h(k)) (1)

C_{mean}= mean(h(k)) (2)

$$Cavg = \frac{Cmedian + Cmean}{2} \quad (3)$$

Sub-image PDF calculation

Each sub-image's PDF, I_1, I_2, I_3, and I_4 is calculated using following Equations.

$$Pl1 = \frac{hcl(k)}{Nl1}, \text{for } 0 \le k \le E_{tlow} \quad (4)$$

$$Pl2 = \frac{hcl(k)}{Nl2}, \text{for } E_{tlow} + 1 \le k \le E_t \quad (5)$$

$$Pu1 = \frac{hcl(k)}{Nu1}, \text{for } E_t + 1 \le k \le E_{tup} \quad (6)$$

$$Pu2 = \frac{hcl(k)}{Nu1}, \text{for } E_{tup} + 1 \le k \le L - 1 \quad (7)$$

Here, N_{l1},N_{l2},N_{u1},N_{u2} are the quantities of pixels found in sub-mages I_1,I_2,I_3,I_4respectively.

Histogram Bin Modification

First of all, PDF for the sub-histogram i can be expressed

$$PDF_{sub\ i,4} = \frac{sub^{i,4}}{n_{i,4}} \quad (3.8)$$

In above Equation, ni,4 is the number of pixels in the sub-histogram i. MVSIHE applies a histogram bin modification to overcome the domination of high frequency intensity levels and to balance high frequency and low frequency intensity levels [16]. Histogram bin modification is given in below equation.

$$MOD\_PDF_{sub\ i,4} = \left(\frac{e^{PDF}_{sub\ i,4} - e^{-PDF}_{sub\ i,4}}{e^{PDF}_{sub\ i,4} + e^{-PDF}_{sub\ i,4}} \right) \quad (3.9)$$

In above Equation, e is the exponential function. Cumulative distribution function(CDF) of the each sub-histogram is then calculated using following Equation.

$$CPDF_{sub\ i,4(X)} = \sum_{j=I^{i,4}_{lowb}}^{I^{i,4}_{upb}} MOD\_PDF(j), \quad \text{for } x = I^{i,4}_{lowb}, \ldots\ldots\ldots I^{i,4}_{upb} \quad (10)$$

Histogram Equalization

HE is applied to each sub-histogram separately instead of global HE. A transformation function which considers the upper and lower boundaries of the sub-histogram is used in this case. Hence, a scaled HE is made and each of the intensity levels is equalized in its own range. Below Equation is employed for this purpose.

$$f_{sub\ i,4(X)} = I^{i,4}_{lowb} + (I^{i,4}_{upb} - I^{i,4}_{lowb}) \times CDF_{sub\ i,4(X)}, \text{for } x = I^{i,4}_{lowb}, \ldots\ldots\ldots I^{i,4}_{upb} \quad (11)$$

After each sub-histogram is equalized, they are merged to generate the final image.

Proposed Cost Function

A cost function in image enhancement is a mathematical expression that quantifies the difference between an enhanced image and the desired outcome. The goal is to minimize this cost function, guiding the enhancement process to improve image quality. Typically, a cost function in image enhancement consists of several components:

1. **Data Fidelity Term**: Ensures the enhanced image remains close to the original or reference image by minimizing the difference between them. This is often represented as the L1 or L2 norm.
2. **Regularization Term**: Introduces penalties to enforce desired properties, such as smoothness or edge preservation, in the enhanced image. Common regularization techniques include Total Variation (TV) for smoothness and L1 norm for sparsity.
3. **Perceptual Quality Term**: Directly measures perceptual aspects of image quality, like sharpness or structural similarity (SSIM), ensuring the enhanced image is visually appealing.

The overall cost function might combine these terms, each weighted according to its importance. By optimizing this cost function using techniques like gradient descent or metaheuristic algorithms, the image enhancement process iteratively adjusts parameters to achieve the best possible image quality. The design of the cost function is crucial as it directly influences the enhancement results, balancing different aspects like fidelity, regularity, and perceptual quality.

Cost function 1

Each member of the population is evaluated using the determined fitness function with respect to the problem type. Because it is tried to enhance images using COA in this study, fitness function should be opted such that minimum distortion occurs in the resultant images. With this motivation, we selected

BRISQUE and NIQE, which are developed to measure quality without needing any reference for various kind of distorted images.
BRISQUE [17] comprises three stages: extracting natural scene statistics (NSS), computing feature vectors and training support vector machines (SVM) [19] for predicting image quality scores. It is known that distribution of the distorted normalized images are different from the distribution of more natural normalized images. Distribution of the relatively less distorted images usually follow a bell curve therefore deviation from this curve can be perceived as a sign of distortion. Mean Subtracted Contrast Normalization (MSCN) is employed in BRISQUE in order to normalize an image. First, to calculate MSCN coefficients, the image is transformed to a luminance matrix as given below:

$$\hat{\mathrm{I}}(\mathrm{i},\mathrm{j}) = \frac{\mathrm{I}(\mathrm{i},\mathrm{j}) - \mu(\mathrm{i},\mathrm{j})}{\sigma(\mathrm{i},\mathrm{j}) + \mathrm{C}}, \quad \mathrm{i} = 1,2,3,\ldots\ldots,\mathrm{M}, \qquad \mathrm{j} = 1,2,3,\ldots\ldots,\mathrm{N} \qquad (12)$$

In the above Equation, I is the image, M and N are height and width of the image, i and j are spatial coordinates in x-axis and y axis, respectively. C is a small constant that is added for making sure the denominator is not equal to zero. The μ is the local mean field whereas σ is the local variance field. Assume that GB is the Gaussian blur window (GBW) and I is the image, we can compute μ and σ are employing using the following Equations.

$$\mu = GBW * I \qquad (13)$$

$$\sigma = \sqrt{GBW * (I - \mu)^2} \qquad (14)$$

Since distortion also depends on the relationship of the pixels, pair-wise product of MSCN image with a shifted MSCN image is calculated. These pair-wise product images are horizontal, vertical, left-diagonal and right-diagonal. In the second step, the 5 images obtained in the first step (MSCN and pair-wise product images) are employed for feature extraction. MSCN image is fitted to a generalized Gaussian distribution (GGD) whereas pair-wise product images are fitted to an asymmetric generalized Gaussian distribution (AGGD). GGD has two parameters (shape and variance) and AGGD has four parameters (shape, mean, left variance and right variance). Hence, 2 features are obtained from MSCN image and 16 features (4 x 4) are obtained from pair wise product images. The image is downsized by two (half of its original size), the same feature extraction technique is repeated and thus 36 features are gathered. In the last step of BRISQUE, feature vectors as inputs and their quality scores as outputs are fed to SVM and a model is trained. This model is used for predicting image quality score afterwards.
NIQE [18] consists of five phases: extracting NSS, patch selection, patch characterization, fitting patches to the multivariate Gaussian model (MGM) and applying NIQE index. For the first phase, NSS extraction, the process is similar to the NSS extraction in BRISQUE except that NIQE is only trained on the natural images but not distorted images. Hence, NIQE does not depend on any particular distortion type. In the second phase, the image is divided into P × P patches and patches exceeding a threshold T (which is defined as 0.75 in the original study) are selected according to the average local deviation field δL given in the following Equation.

$$\delta_L(t) = \sum \sum_{(i,j)\epsilon patc\ h} \sigma(i,j), \quad t = 1,2,\ldots\ldots,N_P \qquad (15)$$

In the above Equation, i and j are the spatial coordinates belong to patch, t is the patch index, NP is the number of patches, and σ(i, j) is the related variance value. In the third phase, similar to the BRISQUE, GGD and AGGD are employed for fitting and with a downsizing, a total number of 36 features are obtained. In the fourth phase, the NSS features obtained in the previous phases are fitted with an MGM model. MGM density can be given as in the below Equation.

$$\boldsymbol{f(X_1,\ldots,X_k) = \frac{1}{(2\pi)^{\frac{k}{2}}|\Sigma|^{\frac{1}{2}}} exp\left(-\frac{1}{2}(x-v)^T\Sigma^{-1}(x-v)\right)} \qquad (\mathbf{16})$$

In above Equation, (x1, ..., xk) are the features, Σ is the covariance matrix and v is the mean. In the last phase, the quality of the distorted images can be computed using the following Equation.

$$\boldsymbol{D(V_1,V_2,\Sigma_1,\Sigma_2) = \sqrt{\left((V_1-V_2)^T\left(\frac{\Sigma_1+\Sigma_2}{2}\right)^{-1}(V_1-V_2)\right)}} \qquad (\mathbf{17})$$

In the above Equation, v1 and v2 are the mean vectors whereas Σ1 and Σ2 are covariance matrices of natural MVG model and distorted image, respectively.
We have used BRISQUE and NIQE together by multiplying their outputs. The results of this multiplication is opted as the fitness function for a minimization problem. Because as the BRISQUE and NIQE scores increase, the quality of the evaluated images are decreased. We have used these metrics together to take advantage of the powerful sides of them. The preferred fitness function is defined in the following Equation.

$$\boldsymbol{F(I) = BRISQUE(I) \times NIQE(I)} \qquad (\mathbf{18})$$

3.6.2 Cost Function 2

The medical images are noisy and have poor contrast. Additionally, there is higher information loss in the improved medical imaging. Additionally, maintaining the image feature after improvement is quite challenging. Therefore, using metrics like contrast, information contents (entropy), PSNR, edge contents, and energy, a novel fitness function has been developed in this article. Therefore, a multi-objective function is used to represent the suggested cost function 2 in this work. Every cost function is given the same weight. However, the definition of the first objective function is

$$cff = log(^{(I_{cont} \times exp(I_{ent}))}/_{I_{ent}} \qquad (19)$$

The final cost function(F) is taken from the two cost functions discussed in this section is obtained as

$$F = {}^{F(I)}/_{cff} \qquad (20)$$

The final cost function is expressed as

$$\mathrm{F} = \frac{\mathrm{BRISQUE(I)} \times \mathrm{NIQE(I)}}{\log\left(^{(\mathrm{I_{cont}} \times \exp(\mathrm{I_{ent}}))}/_{\mathrm{I_{ent}}}\right)} \quad (21)$$

4. RESULTS

The convergence curve of a cost function in image enhancement typically shows how the cost (or loss) function decreases over time as an optimization algorithm iterates. This curve is important for understanding how quickly and effectively the algorithm is minimizing the error and improving the image. In this method we are trying minimise the cost function.

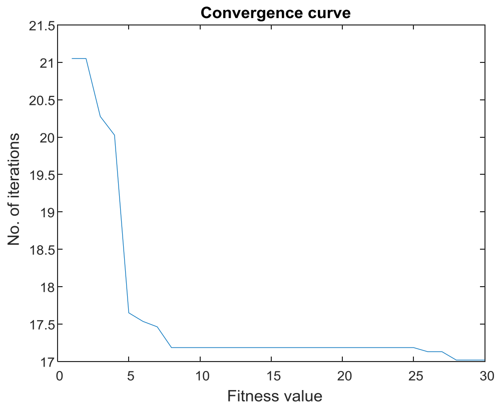


Fig 4. Convergence Curve for Cost function

The above shows how the cost function is minimizing for the number of iterations vs fitness value.

5. CONCLUSION

In this study, we explored the critical role of cost functions in the optimization-based enhancement of medical images, demonstrating their importance in improving image quality while preserving diagnostic accuracy. The results indicate that carefully designed cost functions, which account for medical-specific parameters such as contrast, edge preservation, and signal-to-noise ratio, can significantly enhance the clarity and usability of medical images across various imaging modalities like MRI, CT, and ultrasound. Optimization techniques, including gradient-based methods and deep learning approaches, were shown to effectively minimize these cost functions, leading to improved visibility of clinically relevant structures without introducing distortions or artifacts.

REFERENCES

[1] D. Nirmala, Medical image contrast enhancement techniques, Res. J. Pharm. Biol. Chem. Sci. 6 (3) (2015) 321–329.
[2] P. Kandhway, A.K. Bhandari, A. Singh, A novel reformed histogram equalization based medical image contrast enhancement using krill herd optimization, Biomed. Signal Process. Control 56 (2020), 101677.

[3] V. Todorov, R. Kountcheva, Adaptive approach for enhancement the visual quality of low-contrast medical images. Advances in Intelligent Analysis of Medical Data and Decision Support Systems, Springer, Heidelberg, 2013, pp. 69–78.

[4] B. Subramani, M. Veluchamy, Fuzzy contextual inference system for medical image enhancement, Measurement 148 (2019), 106967.

[5] U.K. Acharya, S. Kumar, Particle swarm optimized texture based histogram equalization (PSOTHE) for MRI brain image enhancement, Optik (2020), 165760.

[6] R.C. Gonzalez, R.E. Woods, Digital Image Processing (3), Prentice Hall Press, Upper Saddle River, NJ, USA, 2002.

[7] Y.T. Kim, Contrast enhancement using brightness preserving bi-histogram equalization, IEEE Trans. Consum. Electron. 43 (1) (1997) 1–8.

[8] Y. Wang, Q. Chen, B. Zhang, Image enhancement based on equal area dualistic sub-image histogram equalization, IEEE Trans. Consum. Electron. 45 (1999) 68–75.

[9] S.D. Chen, A.R. Ramli, Minimum mean brightness error bi-histogram equalization in contrast enhancement, IEEE Trans. Consum. Electron. 49 (4) (2003) 1310–1319.

[10] K. Singh, R. Kapoor, S.K. Sinha, Enhancement of low exposure images via recursive histogram equalization algorithms, Optik 126 (20) (2015) 2619–2625.

[11] K. Singh, R. Kapoor, Image enhancement via median-mean based sub-image-clipped histogram equalization, Optik 125 (17) (2014) 4646–4651.

[12] H. Deng, X. Sun, M. Liu, C. Ye, X. Zhou, Image enhancement based on intuitionistic fuzzy sets theory, IET Image Process. 10 (10) (2016) 701–709.

[13] M. Agarwal, G. Rani, V.S. Dhaka, Optimized contrast enhancement for tumor detection, Int. J. Imaging Syst. Technol. (2020). 12 Optik 230 (2021) 166273 U.K. Acharya and S. Kumar

[14] C.M. Chen, C.C. Chen, M.C. Wu, G. Horng, H.C. Wu, S.H. Hsueh, H.Y. Ho, Automatic contrast enhancement of brain MR images using hierarchical correlation histogram analysis, J. Med. Biol. Eng. 35 (6) (2015) 724–734.

[15] V. Anoop, P.R. Bipin, Medical image enhancement by a bilateral filter using optimization technique, J. Med. Syst. 43 (8) (2019) 240.

[16] B. Subramani, M. Veluchamy, MRI brain image enhancement using brightness preserving adaptive fuzzy histogram equalization, Int. J. Imaging Syst. Technol. 28 (3) (2018) 217–222.

[17] K. Singh, D.K. Vishwakarma, G.S. Walia, R. Kapoor, Contrast enhancement via texture region based histogram equalization, J. Mod. Opt. 63 (15) (2016) 1444–1450.

[18] T.L. Tan, K.S. Sim, C.P. Tso, Image enhancement using background brightness preserving histogram equalisation, Electron. Lett. 48 (3) (2012) 155–157.

[19] L. Rundo, A. Tangherloni, M.S. Nobile, C. Militello, D. Besozzi, G. Mauri, P. Cazzaniga, MedGA: a novel evolutionary method for image enhancement in medical imaging systems, Expert Syst. Appl. 119 (2019) 387–399.

[20] U.K. Acharya, S. Kumar, Image enhancement using exposure and standard deviation-based sub-image histogram equalization for night-time images, in: Proceedings of International Conference on Artificial Intelligence and Applications, Springer, Singapore, 2020, pp. 607–615