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Fuzzy based dynamic histogram equalization for enhancing quality of registered medical image

T. O. Sunitha[1*], R. Rajalakshmi[2], and S. S. Sujatha[3]

[1]Research Scholar, Reg No:18133152282014, Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu - 627012, India.
[2]PG Department of Computer Science, Noorul Islam College of Arts and Sciences, Kumaracoil, Tamil Nadu – 629175, India.
[3]Department of Computer Applications, S.T. Hindu College, Nagercoil, Tamil Nadu - 629002, India

[*]Corresponding author; E-mail: sunithavimal80@gmail.com

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Abstract

Contrast enhancement is considered as significant aspects in medical analysis because the diagnosis error can be minimised only on utilizing better quality image. In addition to, for performing more accurate and detailed analysis the concept of registration is also included. Many scholars had been focusing on registration approaches to perform their research because of its surplus requirement in medical field. But, the existing registration technique lack in preserving the complementary information and quality of images. Thus, to maintain the features of the original image, the proposed method is designed through coupling contrast enhancement technique along with registration. Initially, in this proposed work, the scanned medical image is taken as input. To improve the quality of image fuzzy employed dynamic histogram equalization is utilized. In this approach initially the histogram of the input image is partitioned based on fuzzy rule. Then, the resultant sub-histogram are equalized based on dynamic range. The final output of this approach is quality enhanced image. Then, registration of this quality enhanced image is attained based on Multi-Scale Singular Value Decomposition (MSVD). The entire proposed architecture is implemented in the MATLAB platform, and the process is compared with the existing approach. Some of the performance metrics, such as average mean brightness error, image contrast, information content and execution time for the proposed method is 0.3345, 242, 5.6 and 36.14 sec. This analysis shows superior performance of the proposed registration induced with contrast enhancement on comparison with existing. Based on this proposed approach high quality image is obtained with less information loss to support medical experts for accurate diagnosis.

Keywords*: Contrast enhancement; FEDHE; Medical image; More informative; MSVD; Quality; Registration.*

1. Introduction

Medical image processing faced a lot of advancement over past years, and this results in huge changes in treatment and surgery offered to the patients. Through introducing the art of computer technology, conventional surgery had been altered to computer-assisted surgery (CAS). Normally, this CAS utilizes some of the medical image processing methods for monitoring the diseases, planning for treatment as well as diagnostic purposes. Through the inclusion of this kind of method in diagnosis, fast recovery of patients decreased surgical pain and reduction in cost can be achieved. Due to these prevailing advantages at present, medical providers are focusing on these technologies for offering effective treatment and diagnosis. However, during surgery, real-time visualization of images captured from different medical devices and various time frames is essential. Because the information contained in a single image is not enough for surgery, to fulfil this requirement, the process of image registration is introduced (Ayhan et al., 2017).

The process of mapping or geometrical alignment of pixels points in two different images is referred to as image registration. Through registered images, more information that is necessary for effective surgery can be reached. The most significant challenge faced in the image registration technique is the attainment of better quality images. Many researchers are focusing on the domain of image registration for achieving better quality images with more information (Liu, Cheung, Cheng, Su & Leach, 2017). In order to attain a high-quality image, the idea of contrast enhancement can be included. Contrast enhancement is a pre-processing technique included in image processing methods for improving the quality of the image by reducing the noise effect. Mostly widely used conventional approach for contrast enhancement is Histogram Equalization (HE). This conventional method faces a problem of artifacts and an unnatural look of the image due to the presence of some dominant features. To overcome such limitations, Dynamic Histogram Equalization (DHE) is utilized.

In DHE, before histogram normalization, a certain dynamic range is fixed. Therefore, no dominant features will be present, and the brightness of the image will be preserved. Some of the conventional contrast enhancement technique includes Segment Selective Dynamic Histogram Equalization (SSDHE), Brightness Preserving Histogram Equalization (BPHE), Adaptive Histogram Equalization (AHE), Bi-Histogram Equalization (BHE), Multi- Histogram Equalization (MHE) etc. (Liu, Zhou, Chen & Kang, 2017). However, an enhanced quality image with more information is not attained in any of the existing frameworks. To achieve a high-quality greyscale image, fuzzy employed DHE is designed in this proposed architecture. After that, with the help of a contrast-enhanced image, the process of registration is performed using Multi-Scale Value Decomposition (MSVD) (Priyadharsini, Sharmila & Rajendran, 2018). Finally, the obtained registered image will be of high quality and more information. Using this enhanced registered image, the medical examination and treatment can be done more accurately.

1.1. Related work

Numerous researches by various researchers had been performed in the area of registration and contrast enhancement of images. And, only a few articles were found related to medical images analysis. Here, the research work is reviewed in two categories. In the first category, the articles related to some of the existing contrast enhancement techniques in the image will be surveyed. Subsequently, in the second category, some of the conventional articles related to the registration process will be reviewed.

1.1.1. Review on Contrast Enhancement Technique

Adaptive gamma correlation with weighted histogram distribution was designed by Veluchamy and Subramani (2019, 2020) to improve the contrast of the image as well as to preserve the colour of the image. Because traditional HE methods suffered from saturation effect in intensity level and over-enhancement. In the designed approach, gamma correlation focused on contrast enhancement while weighted histogram normalization focused on colour preservation (Yang, Dan, & Yang, 2018). A hybrid of deep learning and traditional contrast enhancement technique was done by Fu and Cao (2020) to enhance the contrast of underwater images. The underwater image had the issue of decreased contrast and colour distortion because of the scattering effect. To solve this issue global-local network was designed. Local entropy employed weighted histogram distribution was developed by Wan et al. (2018) to improve the contrast of infrared images. In this local entropy-based approach, the histogram was partitioned into two sub-histogram based on threshold values. To determine the threshold value, a particle swarm optimization algorithm was utilized (Abdel-Basset, Fakhry, El-Henawy, Qiu, & Sangaiah, 2017; Kanmani & Narsimhan, 2018; Wan et al., 2018).

Sharp edge enhancement framework along with krill herd optimization was introduced by Kandhway and Bhandari (2019) for enhancing the contrast of the medical image. The adjustable parameter considered in this present approach included entropy, edge, Grey Level Co-Occurrence Matrix (GLCM) and GLCM energy. By means of adjusting the above mentioned parameter contrast of the image can be improved. Adaptive thresholding employed sub-histogram normalization method was designed by Kandhway, Bhandari and Singh (2020) to enhance the contrast of the image along with preserving the image brightness. In this approach also the histogram is divided into sub-histogram based on the threshold intensity. The threshold value is not pre-defined and it found based on peak-signal to noise ratio. To evaluate the attainment of contrast in the image certain contrast enhancement parameters such as modified enhancement measure and contrast per pixel. Huang et al. (2021) developed contrast limited dynamic quadri-histogram equalization for enhancing the contrast of medical images. Based on this developed approach some of the limitations prevailing in conventional techniques such as over smoothing and over enhancement can be solved. This present approach obtained pleasing outcome by means of preserving the brightness of the structure.

1.1.2. Review on Existing Registration Methods

Image registration process based on RANSAC (RANdom Sample Consensus) transform and SIFT (Scale Invariant Feature Transform) features was designed by Hossein-Nejada and Nasri (2017) to overcome the inconsistency faced in image registration. Normally to determine the irrelevant features in the image RANSAC transform was utilized. After that to find the matching features in the image SIFT transform was used. Deep learning based Convolutional Neural Network (CNN) was designed by de Vos et al. (2019) to perform registration on medical image. The designed deep learning architecture was utilized for deformable registration as well as for affine registration (Ferrante, Dokania, Silva & Paragios, 2018). And the training process in CNN was achieved using Deep Learning Registration Framework (DLRF). The designed deep learning architecture mainly focused in medical images. CNN was designed by Yang, Yang, Yang, and Wei (2018) to perform registration in remote sensing images. Initially, the designed deep CNN extracted the features disturbed in the image. Then, the selection of inilier was gradually improved to enhance the registration.

Deep reinforcement learning based image registration was designed by Ma et al. (2017) for automatic alignment of MRI image with CT scan image. The optimal process contained in this present work was extracting the relevant features from the image. Accelerated Binary Robust Invariant Scalable Keypoints method was designed by Tsai and Lin (2017) to attain registration of vehicle surveillance images. The present design had utilized feature descriptors to match the relevant features and to determine the mismatch features sorting ring method was utilized. Fast adaptive bidirectional empirical mode decomposition method was introduced by Guryanov and Krylov (2017) for achieving robust registration of medical image (Zachariadis et al., 2020). With the help of this designed approach computation complexity faced by mutual entropy maximization algorithm can be reduced (Punithakumar, Boulanger & Noga, 2017). And this developed approach can also be utilized for multimodal image registration. Wei Shao et al (2021) developed a ProsRegNet framework for registration of histopathology and MRI images related to prostate. This designed framework functioned on the basis of affine and deformable transform estimation through deep learning approach. Further the designed framework can improve the accuracy of prostate cancer detection.

1.1.3 Problem formulation

Some of the literature articles that were explained previously focused on registration and contrast enhancement separately (Gupta & Tiwari, 2019). The major problem faced in contrast enhancement is over- enhancement and saturation intensity which results in extreme brightness. On the other hand the major drawback faced in registration is inappropriate matching of features because of less information in image. To solve these issues the proposed framework was designed by coupling contrast enhancement technique along with registration. The proposed architecture will be englutted in the third section.

2. Objective

The major motive of this present research work will be described below,

- To perform more detailed and accurate analysis on medical image the process of image registration is introduced.
- To overcome the issue of diagnosing using single medical image, both CT and MRI images are merged together with proper alignment.
- For attaining registered images, MSVD based decomposition algorithm is utilized.
- To achieve high quality registered image, a contrast enhancement technique is employed along with registration.
- To reach a high-quality image, fuzzy rule-based dynamic histogram equalization is developed.
- To attain better quality image without much information loss the proposed contrast enhancement based registration technique is designed.

3. Methodology

3.1 Organization of the work

The remaining portion of the research article is arranged as follows. The second part of the manuscript will illustrate the research work studied related to the registration and contrast enhancement process. Following that, the third portion of the manuscript will discuss the outline of the proposed architecture. The fourth part of the research article will elaborate on the proposed framework in a detailed manner. The fifth part of the article will discuss the results acquired through execution. Finally, the sixth portion will end with a conclusion.

3.2 Proposed methodology

Normally, image registration is the process of special alignment of two images captured from different devices or different imaging protocols. The research in the approach of image registration is growing rapidly because of its numerous benefits in various field of application. In addition to it, it plays a significant role in the field of medicine. Through registration process in medical field images captured from different devices such as CT and MRI can be coupled together and the analysis can also be done more accurately as well as in detailed manner. Despite of various benefits, the process of image registration has certain challenges which includes computation complexity, time consumption and less accuracy. The prevailing challenges in registration is due to presence of blurriness' and noise effect in medical image. To overcome the above mentioned challenges the proposed framework had introduced contrast enhancement technique along with registration. And the proposed registration approach is analyzed in two different scenario. The first scenario is registration with contrast enhancement and second scenario is registration without contrast enhancement. The schematic representation of proposed image registration method is given in Figure 1.

The proposed architecture is designed based on two stages. The first stage is contrast enhancement. In this stage the clarity and brightness of the image get improved. Following that the second stage is registration in which the mapping of two images will be done for acquiring more information for detailed analysis. The initial step considered in this proposed architecture is providing the input image. The input image considered for this proposed design is brain image captured using MRI and CT scan. Once the input image is taken, the second step is pre-processing. The pre-processing of image is done to improve its contrast to attain accurate results. The method of contrast enhancement in this proposed design is done based on Fuzzy Employed Dynamic Histogram Equalization (FEDHE). The output obtained as a result of contrast enhancement technique is considered for further analysis. Subsequently in third step the process of registration is performed using Multi-scale Singular Value Decomposition (MSVD). In MSVD technique, high frequency and low frequency components are separated using filtering technique and then the salient information present in that frequency components are extracted and combined together. Finally, the function of inverse decomposition is carried out to obtain the registered image (Yue, Yang, Sun, Wu, & Hou, 2017). The final output of this proposed framework is registered image with improved contrast. Further, the analysis in this proposed work is carried out in two different scenario as explained previously to evaluate its performance. The proposed registration approach with the application of contrast enhancement technique will be elaborated in the proceeding section.

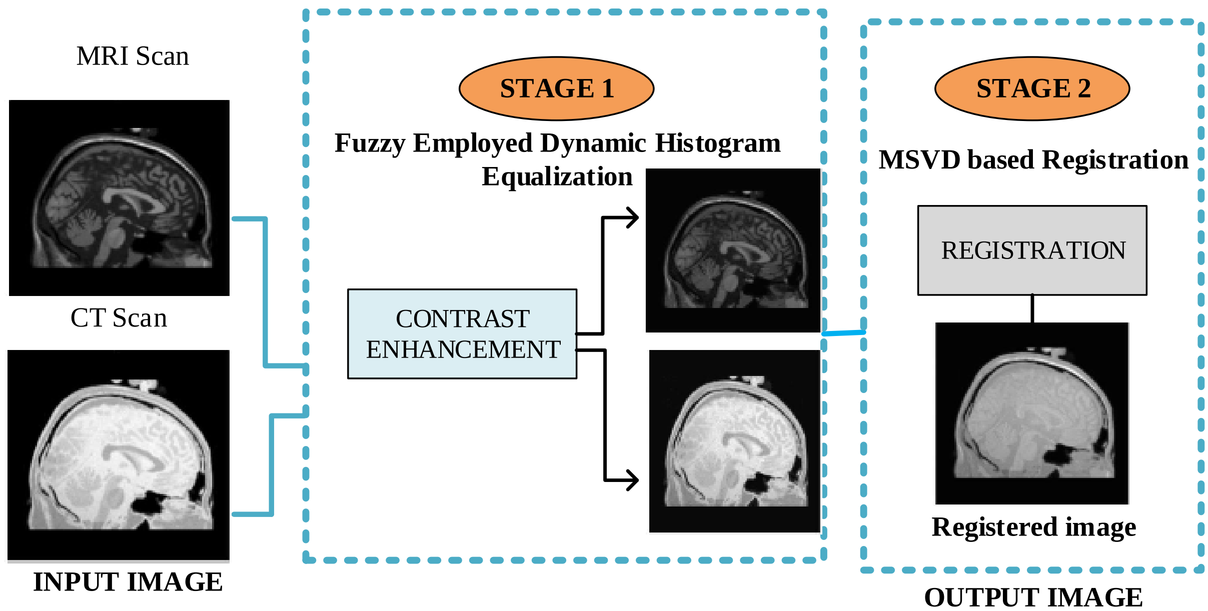


Figure 1 Schematic representation of proposed framework

3.3 Elaboration of proposed architecture

The main objective of this proposed framework is to improve the quality of the medical images for achieving detailed analysis. The quality of the medical image can be improved through performing the process of contrast enhancement. The most commonly used method for image contrast improvement is Histogram Equalization (HE). But the traditional histogram equalization led to extreme equalization which results in unnatural look of the image. The extreme equalization is reached due to domination of some part of the histogram. To solve this kind of issue in traditional histogram method, fuzzy based dynamic histogram is used in this proposed work for enhancing the contrast of the image. Further the contrast enhanced image is decomposed using MSVD to obtain the registered image. The sequence of steps involved in this proposed architecture will be discussed briefly in the below section.

3.3.1. Dataset collection

The dataset considered for this present analysis is medical images. The medical images include heart, lungs, brain, neck and so on. The present work is focused on brain image. The images captured from different medical devices such as MRI and CT scan is considered. In CT scan, the overall problem in bones, tissues and body organs can be analyzed. Whereas in MRI scan, the detailed study on every parts of the body can be done. The process of registration is performed for mapping the information captured through both the scan such as MRI and CT in order to carry out more accurate and detailed analysis. Through detailed analysis, the treatment for the corresponding patients can be done effectively. At last the brain images captured from CT and MRI scan is considered for further analysis.

3.3.2. Stage 1: contrast enhancement

Once the image necessary for analysis is collected, the next step is to enhance the quality and brightness of the image by means of contrast enhancement technique. The contrast enhancement in image is attained through altering its pixel intensity. This technique has wider range of application starting from medical image till radar image processing. The frequently used technique for attaining contrast enhanced image is Global Histogram Equalization (GHE). The computation of GHE is quite simple and it also achieves better performance for various images. Despite of its several advantage it has certain limitation such as occurrence of foremost alteration in grey level of image during equalization of the histogram. At the same time the mean brightness of the image is impossible to be conserved. This results in presence of extreme spikes in the histogram peaks. For solving this kind of limitations in GHE, several technique had been emerged for equalizing the histogram. In this proposed framework Fuzzy Employed Dynamic Histogram Equalization (FEDHE) is utilized for attaining better contrast enhancement of the image. The working principle behind FEDHE will be conferred briefly in the following section.

3.3.2.1 Fuzzy employed dynamic histogram equalization

Generally, in traditional histogram method, while mapping the histogram local maxima there is possibility for occurrence of unwanted artifacts as well decrease in brightness of the image. To overcome unwanted artifacts and to improve the brightness of the image proposed FEDHE is utilized. The process flow involved in this designed contrast enhancement technique will be clarified as follows. The process layout of fuzzy based dynamic histogram equalization is given in Figure 2.

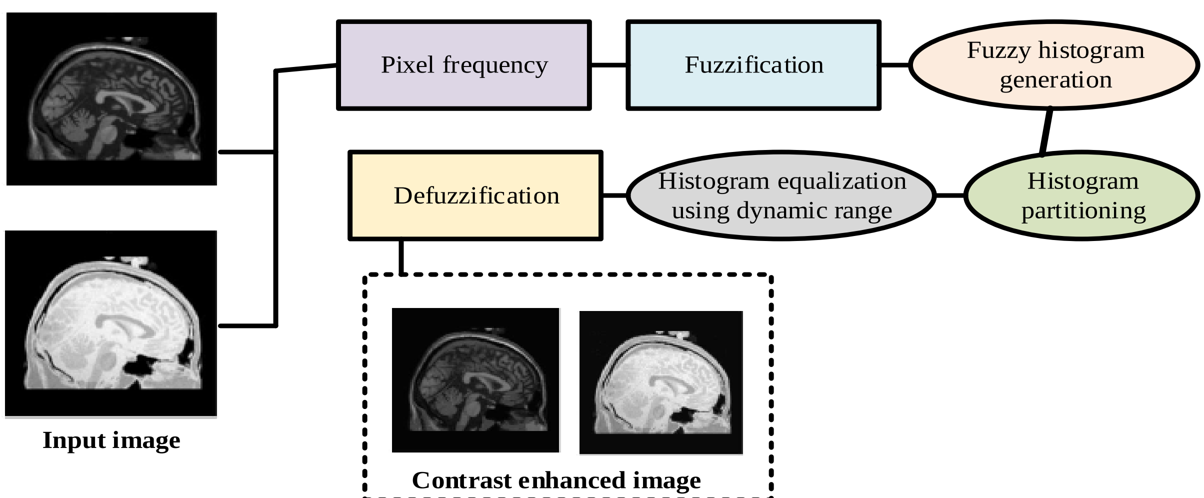


Figure 2 Fuzzy employed dynamic histogram equalization

Initially in this proposed FEDHE approach, fuzzy histogram is generated from normal histogram with the help of fuzzy logic model (Sheet, Garud, Suveer, Mahadevappa, & Chatterjee 2010). Through including fuzzy logic in normal histogram the inexactness in grey values can be handled in an effective way. In second step the median value for the original image is calculated and based on that value the created fuzzy histogram is classified into sub-histogram. Finally, every sub-histogram is applied within the created fresh dynamic range. The pseudo code explaining the fuzzy dynamic histogram equalization is specified below.

Pseudo code of fuzzy dynamic histogram equalization

At first, medical image of CT and MRI is taken as input
Calculate the pixel frequency ($F_{(a,b)}$)of the original images
Create histogram for the original image
Convert the pixel frequency into fuzzy value $(0,1)$
If $(F_{(a,b)}) < 0.5$
a= dark
Else
b=bright
End if
Generation of fuzzy histogram based on equation (2)
Partitioning of histogram based on M into H_L and $H_U$according to equation (3)
Equalize the histogram based on dynamic range as given in equation (6)
Terminate the process once the histogram get equalized

Step 1: ***Creation of Fuzzy Histogram***

In this step, at the beginning the pixel intensity of original image was mapped to fuzzy value in the range between zero and one. The process of mapping of original pixel value to fuzzy value is referred to as fuzzification. For instance the image with size $A \times B$ has the intensity value in the range (0, R-1). These intensity level are noted as fuzzy set along with membership function. The membership function in this approach is framed based on frequency of pixel intensity. The membership function is expressed as follows.

$$F_{f(a,b)}=\begin{cases} 2\times(F_{a,b})^2, & 0\le F_{a,b}\le 0.5 \\ 1-\left(2\times\left(F_{a,b}\right)^2\right), & 0.5<F_{a,b}\le 1 \end{cases} \quad (1)$$

Equation (1) represents the fuzzy membership function framed with the help of pixel frequency. $F_{a,b}$ represents the frequency of pixel values. If the value of $F_{a,b} = 0$ then it denotes dark on the other hand if the value of $F_{a,b} = 1$ then it indicates bright. Through introducing the concept of fuzzy, smooth histogram can be obtained (Saravanan & Karthigaivel, 2021). Finally, based on this membership function the fuzzy histogram is generated. The equation representing the computation of fuzzy histogram is enlightened in equation (2).

$$H\leftarrow h(i)+\sum_a\sum_b F_{f(a,b)} \quad (2)$$

In the above equation $F_{f(a,b)}$ denotes the fuzzy membership function, $h(i)$ signifies the normal histogram and H represents the computated fuzzy histogram.

Step 2: ***partitioning of histogram***

Once the fuzzy histogram is generated the next step is to partition the histogram. The histogram is partitioned based on median value. The median value is calculated for the input image. And on the basis of this median value the histogram is split into two sub histograms. The mathematical expression describing the partitioning of histogram is given in equation (3).

$$H=H_L\cup H_U \quad (3)$$
$$H_L=\{H(a,b)|H(a,b)\le M\} \quad (4)$$
$$H_U=\{H(a,b)|H(a,b)>M\} \quad (5)$$

The two sub histograms computed from fuzzy histogram is given in equation (4) and (5). H_L represents the lower sub histogram, H_U represents upper sub histogram, M signifies the median value based on which the histogram is partitioned and $H(a,b)$ denotes the pixels in the histogram.

As the partitioning of histogram is performed based on median value, the histogram with lower median value comes under one category and the histogram with higher median value will come under second category. Using this criteria the histogram is classified into sub histogram.

Step 3: ***equalization of histogram based on dynamic range***

The equalization of sub-histogram is performed individually using dynamic histogram equalization method. For equalizing purpose spanning function is used. The spanning approach is designed on the basis of number of pixels entirely present in the histogram. The formulae used for representing the spanning function is illustrated in equation (6), (7) and (8).

$$span_a = high_a - low_a \tag{6}$$

$$factor_a = span_a \times log_{10} M_a \tag{7}$$

$$range_a = \frac{(R-1) \times factor_a}{\sum_{k=1}^{n+1} factor_k} \tag{8}$$

In equation (6), $high_a$ signifies the highest intensity value in the input sub-histogram, low_a denotes the lowest intensity in the sub-histogram, M_a represents the total number of pixels contained in that specified partition, $span_a$ is used for representing the dynamic range in input sub-histogram whereas $range_a$ is used for signifying the dynamic range of output sub-histogram, $factor_a$ represents the factor calculation for sub histogram, $factor_k$ represents the factor for k^{th} intensity level.

The calculation of dynamic range for output sub-histogram using $range_a$ is given in equation (9) and (10).

$$start_a = \sum_{k=1}^{a-1} range_k + 1 \tag{9}$$

$$stop_a = \sum_{k=1}^{a} range_k \tag{10}$$

The above equation represents the dynamic range $[start_a stop_a,]$for output sub-histogram, $range_k$ denotes the range of k^{th} intensity level. With the help of this dynamic range the equalization of sub-histogram is carried out. Once the histogram is equalized then finally the obtained new intensity value in the form of fuzzy set is remapped to original pixel value. The process of remapping of fuzzy set to original value is termed as defuzzification. As a result of utilizing fuzzy employed dynamic histogram equalization the brightness of the image is preserved and at the same time quality of the image is improved through reducing the artifacts.

3.3.3. Stage 2: MSVD based registration

Once the contrast of the image is enhanced the next step is to decompose the two input image to obtain the registered image. The process of image registration is performed using multi scale decomposition algorithm. Multi scale decomposition based image registration is elaborated briefly in (Sunitha & Rajalakshmi, 2021). The series of step involved in MSVD based registration is discussed as follows.

Step 1: In the beginning of the process brain images acquired from CT and MRI scan is taken. Then, the quality of the image is improved by performing contrast enhancement technique.

Step 2: The contrast enhanced image is further sent for MSVD approach. In MSVD the input image is divided into four sub-band based on the frequency. The four sub-bands are high-high, high-low, low-high and low-low.

Step 3: In this step again the input image is sent into wiener filter where the low frequency components are separated from the image.

Step 4: The low frequency components and input image are added together based on addition rule in order to reach the high frequency components.

Step 5: Further in order to select the optimal high frequency component chicken swarm optimization algorithm is utilized.

Step 6: And to select optimal low frequency components, the components are introduced into salient information.

Step 7: Based on the selected low frequency and high components the register rule is frame.

Step 8: Finally, the inverse of MSVD is done to obtain the registered image.

Based on this proposed framework the registered medical image with better quality is obtained. The ultimate goal of this proposed architecture is to achieve image registration with enhanced quality. For attaining better quality image with more information fuzzy included dynamic histogram equalization is utilized.

3.3.4. Two cases involved in proposed framework

Further the analysis of proposed architecture is carried out in two cases. The two cases involved in this proposed framework will be discussed portrayed as follows. The systematic flow involved in two cases is given in Figure 3.

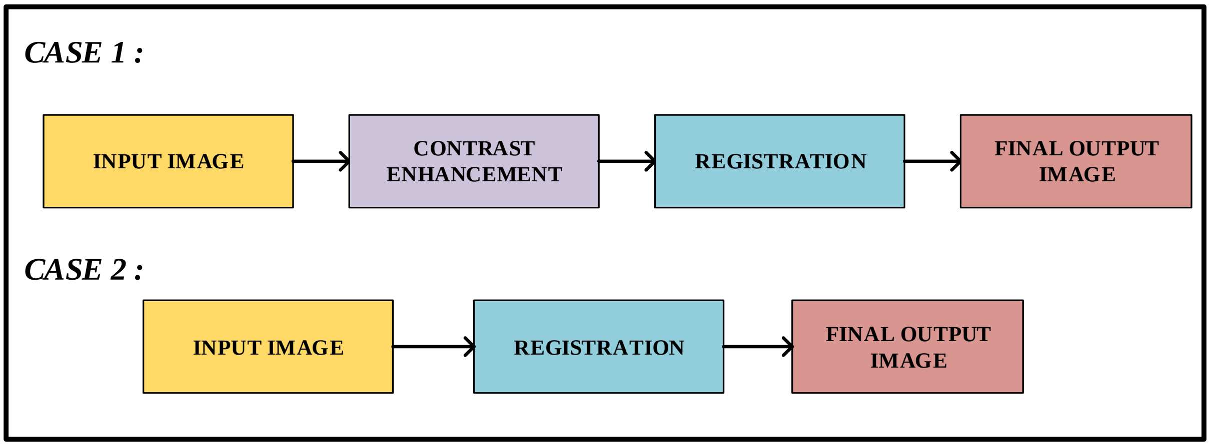


Figure 3 Systematic flow involved in two cases

Case 1: ***Registration with application of contrast enhancement***

In this case, initially the input image is processed with contrast enhancement technique. Then, the brightness enhanced image is sent for further registration process. The registered image will be obtained as final output. The obtained output image will have more information with better quality.

Case 1: ***Registration without contrast enhancement***

In this case, at first input image is taken and it is sent for registration process. The image is not subjected to contrast enhancement technique in this case. Rather it is directly sent for registration process. The final output will be the registered image. The acquired output image in this circumstances will be of less quality and low informative when compared to first case. Additionally, the proposed system is executed in MatLab tool to carry out experimental investigation. The discussion regarding experimental results will be provided in the first section.

4. Results and discussion

The experimental investigation on the proposed framework is carried out in MatLab software with the following system configuration:

- **Processor:** intel core i5-3570s
- **CPU:** 3.10GHz
- **Graphics:** Gallium 0.4 on SVGA3D
- **OS type:** 64 bit
- **Memory:** 974.3 MiB

4.1 Dataset description

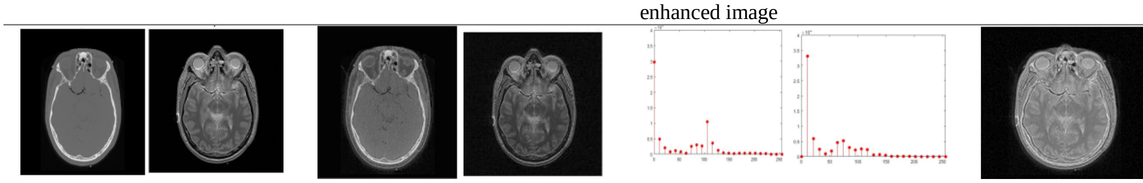
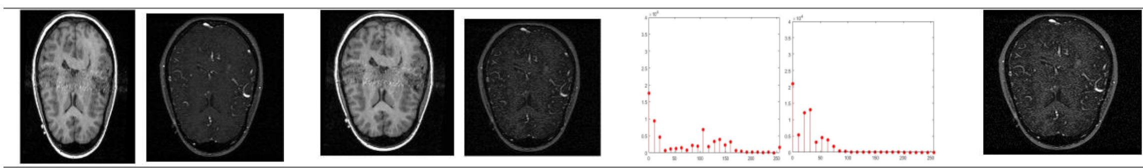
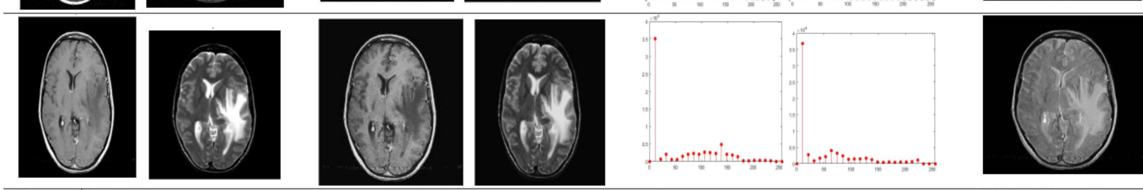
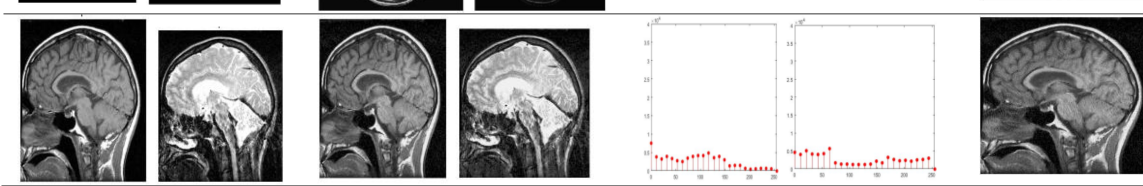
The analysis is performed with the help of dataset collected from web source(Link listed in references). This dataset was created by Durga Prasad Bavirisetti and it consist of images based on remote sensing, visual surveillance and medical images. Out of these images the medical images is considered for this present analysis. These images are multi-modal image captured using various devices in different locations. The size of the entire medical image is 7, 21,080 bytes. Some of the sample medical image taken for analysis is given in Table 1.

Image registration is the ultimate target of this proposed framework. But in conventional approaches the acquired registered image is of less informative and low quality. To improve the quality of the registered image the concept of contrast enhancement is included in this proposed registration approach to improve the quality of the image. The contrast of the image is enhanced using Fuzzy Employed Dynamic Histogram Equalization (FEDHE). Contrast enhanced image is sent for further registration process. The process of image registration in this proposed work is performed using MSVD approach. The final output of this proposed framework is registered image with more information. The analysis of this proposed framework is carried out in two cases. The results obtained in two different cases is explained below.

Case 1: ***Registration with contrast enhancement***

The input image is first subjected to the technique of contrast enhancement in this first case. After applying contrast enhancement technique, the contrast enhanced image is obtained as processed image. Further, the contrast enhanced image is sent for registration process. The image obtained in every step of proposed framework for first case in illustrated in Table 1.

Table 1 Image obtained in every step of proposed framework for case 1

Input image	Contrast enhanced image	Histogram plot for contrast enhanced image	Registered image
			
			
			
			

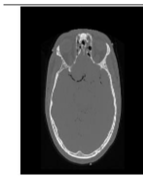
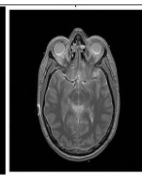
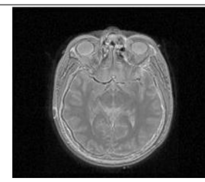
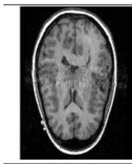
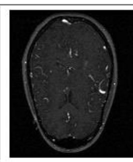
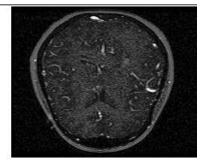
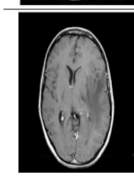
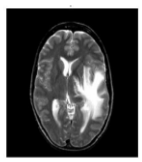
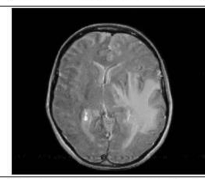
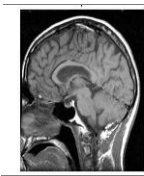
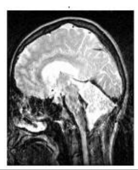
The above Table 1 illustrated the images obtained in every process of the proposed work. Initially, the brain image captured for MRI and CT scan is taken as input. Then, FEDHE is applied to input image. As a result of this approach, the contrast enhanced image is obtained. Along with the contrast enhanced image, the histogram plot acquired for contrast enhanced image is also displayed. The final output image displayed in the previous Table is the registered image.

Case 2: ***Registration without contrast enhancement***

In this second case of analysis the input image is directly sent to the process of registration. The contrast enhancement phase is neglected in this case. The image obtained in every step of proposed framework for second case in illustrated in Table 2.

Table 2 displayed the registered image obtained without contrast enhancement. Initially, the input image captured from MRI and CT scan is taken. Then, these two images are subjected to the process of registration. The final output is the registered image without contrast enhancement. Additionally, to evaluate the performance of the proposed framework some of the performance metrics are evaluated for both the cases. The performance evaluation for the proposed architecture is discussed briefly in the following section.

Table 2 Image obtained in every step of proposed framework for case 1

Input image		Registered image
		
		
		
		

4.2. Performance evaluation

The performance of the proposed architecture is analyzed in this section. To analyze the functioning of designed architecture certain performance parameters are evaluated. The performance metrics that are considered for evaluation includes Average Pixel Intensity (API), Standard Deviation (SD), Average Gradient (AG), Entropy and Mutual Information (MIF) (Jagalingam, & Hegde, 2015). The mathematical expression used for representing these metrics is explained below.

Average Pixel Intensity (API):

It is the sum of entire pixel value to the number of pixels in an image.

$$API=\frac{\sum x}{n} \tag{11}$$

Where, $x$is the pixel value and n in the total number of pixels.

Standard Deviation (SD):

It helps to compute deviation present in the image. The value of SD must be lower and is mathematically given as:

$$SD=\sqrt{\frac{1}{a\times b}\sum_{m=1}^{a}\sum_{n=1}^{b}[f(m,n)-\mu^2]} \tag{12}$$

Where $f(m,n)$represents the fused image and μ defines the fused images mean measure.

Average gradient (AG):

It reflects the image clarity and it should possess lower value so that, better quality image would be obtained.

$$AG(m,)=L\left(\nabla(m)\nabla u(n)\right) \quad (13)$$

Here $u(m)$ and $u(n)$signifies the horizontal and vertical average pixel values.

Entropy (E):

This measure is utilized to compute quality of fused image frame in which the obtained value is lower means, image possess higher information and is given as:

$$E=\sum_{N=0}^{N-1} P_n log P_n \quad (14)$$

The entropy is measured for both the original image as well as reconstructed image in order to determine the loss of information on comparison with original and reconstructed image.

Mutual Information (MIF)

Mutual information is estimated between two variables and it helps in measuring the uncertainity of one variable by knowing the value of other variable.

$$M(x,y)=E(x)\text{-}E\left((x/y)\right) \quad (15)$$

Where, $M(x,y)$ represents the mutual information between two images such as initial input image and final output image, $E(x)$ denotes the entropy of the input image and $E\left((x/y)\right)$ denotes conditional entropy of both the images. The above mentioned metrics are calculated for the proposed framework for six different images.

The metrics like average pixel intensity, standard deviation, average gradient and entropy are lower for the condition (image with contrast enhancement) when compared to other condition. Controversially, the metric such as mutual information is higher for the condition (image with contrast enhancement) on contrast with another. This showed that images subjected to contrast enhancement process is found to be more informative and quality when compared with images that are not subjected to contrast enhancement process. The estimated metrics are represented in graphical format in the below section.

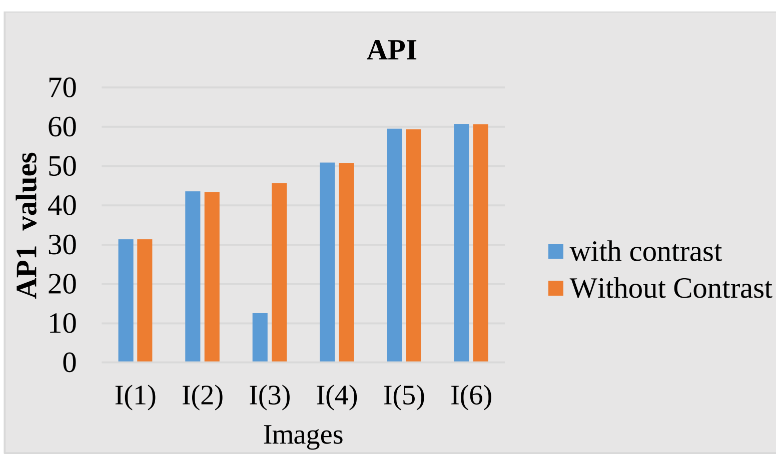


Figure 4 Evaluation of API

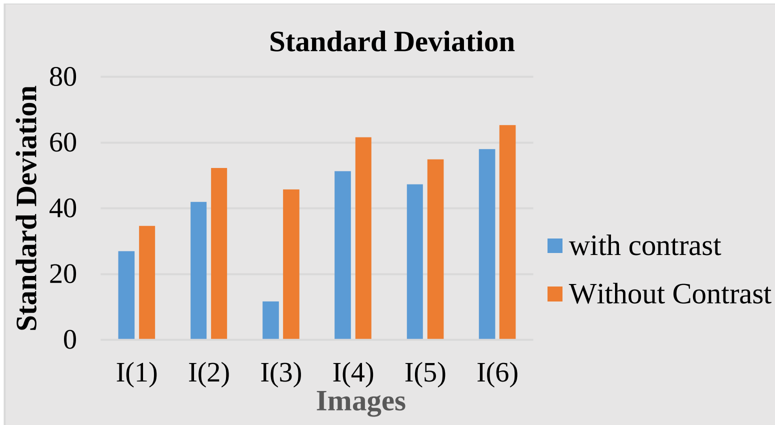


Figure 5 Evaluation of standard deviation

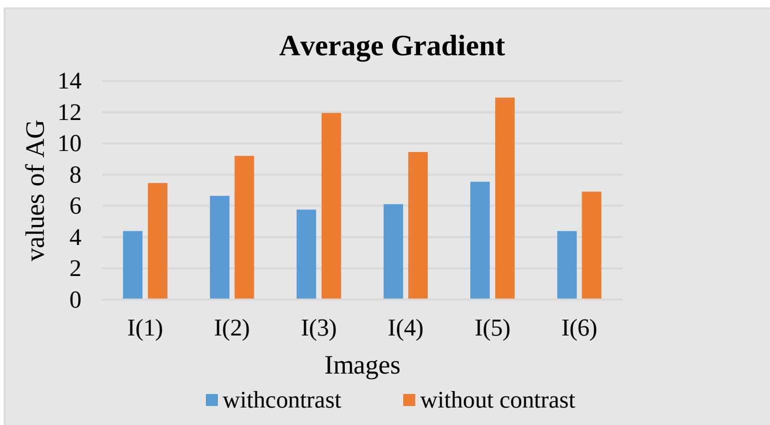


Figure 6 Evaluation of average gradient

The evaluation of the performance metric such as average pixel intensity and standard deviation is represented in Figure 4 and Figure 5. In Figure 4 the graph is sketched between six different images and its corresponding average pixel intensity in X and Y coordinates respectively. The blue bar in the graph corresponds to the values obtained for images with contrast enhancement and the red bar in the graph represents the values reached for images without contrast enhancement process. On comparison the value it is found that average pixel intensity is lower for images when subjected to contrast enhancement process. In Figure 5 the graph is sketched between six different images and its corresponding standard deviation values in X and Y coordinates respectively. Similarly in case of standard deviation also the images subjected to contrast enhancement technique has lower value when compared to images not subjected to contrast enhancement process. . In Figure 6 the graph is sketched between six different images and its corresponding average gradient values in X and Y coordinates respectively. Similarly in case of average gradient also the images subjected to contrast enhancement technique has lower value when compared to images not subjected to contrast enhancement process.

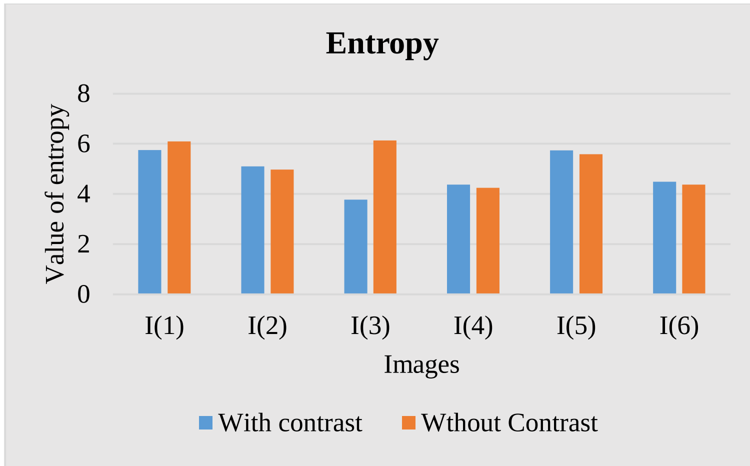


Figure 7 Evaluation of Entropy

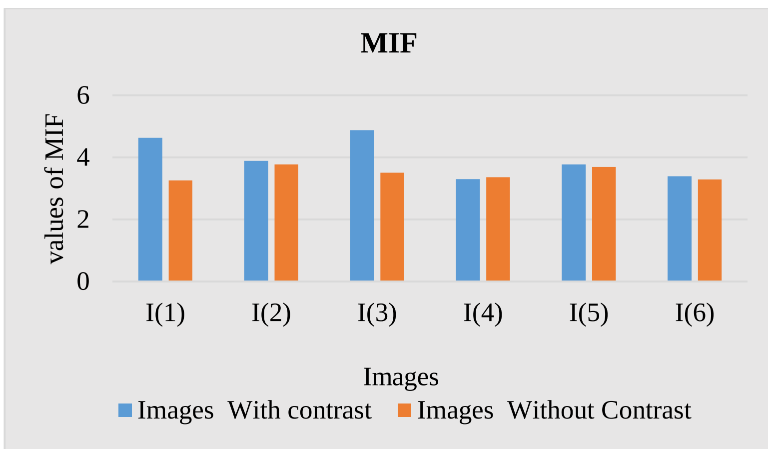


Figure 8 Evaluation of MIF

The evaluation of performance metrics like entropy and MIF is given in Figure 7 and Figure 8. In case of Figure 7 the evaluation of entropy parameter is illustrated. The graph is drawn between entropy and various images on both the axes. Generally, the value of entropy must be lower for effective functioning system. Similarly, the value of entropy for image registration along with contrast enhancement is lower on comparison to images without contrast enhancement. The evaluation of MIF parameter is illustrated in Figure 8. In that also the graph is drawn between six variant of images and MIF values on X-label and Y-label respectively. But in this case the value of MIF is greater for images with enhanced contrast.

The metrics considered for evaluation includes Fusion Symmetry (FS), correlation and Spatial Frequency (SF). These three parameters are lower for image with enhanced contrast on comparison with images without contrast enhancement. These parameters also represented in graphical format as follows.

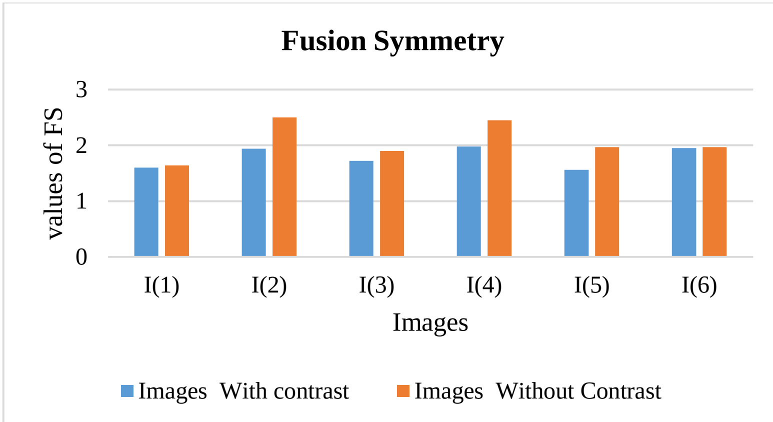


Figure 9 Evaluation of FS

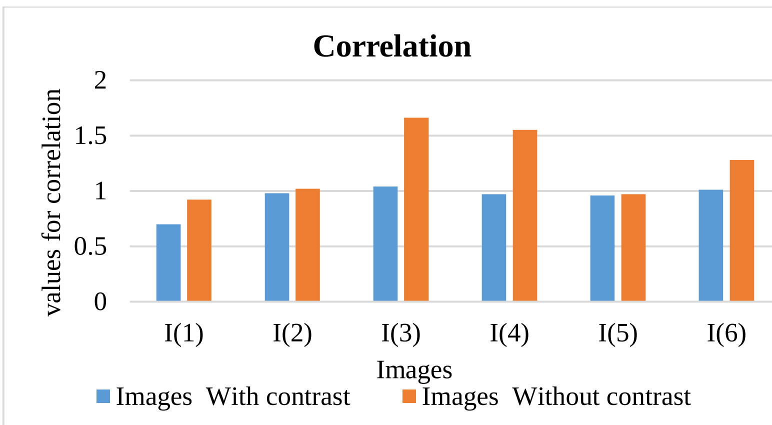


Figure 10 Evaluation of correlation

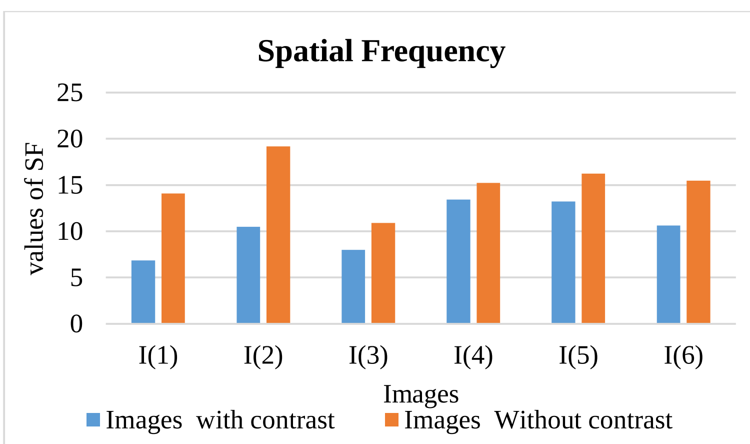


Figure 11 Evaluation of spatial frequency

The evaluation of FS metric is given in Figure 9. The FS metric is also lower for the images subjected to contrast enhancement process. The FS metric lies in the range of 1.5 to 2 for images processed with contrast enhanced technique. And for the images without contrast enhancement process FS metric lies in the range of 2-2.5. The evaluation of correlation metric is given in Figure 10. The correlation factor for images processed with contrast enhancement technique lies in the range of 0.5-1. Whereas for images without contrast enhancement process lies in the range between 1 and 2. In Figure 11 the evaluation of spatial frequency is given. The SF values for images processed with contrast enhancement technique lies between 5 and 14. And for images without contrast enhancement the SF values lies in the range of 15-20. Through evaluating these parameters it is assured that registered images processed with contrast enhancement approach is with better quality when compared with registered images without contrast enhancement process.

4.3. Comparison analysis

In order to prove the superiority of the proposed method are comparison to conventional approaches a comparison is performed. The comparison is carried out to prove the effective functioning of the histogram equalization technique preferred in this proposed framework. The histogram equalization technique utilized in this proposed work is Fuzzy Employed Dynamic Histogram Equalization (FEDHE). The conventional approaches used for comparison includes Segment Selective Dynamic Histogram Equalization (SSDHE) (Khan, Khan, & Abbasi, 2014), Brightness Preserving Histogram Equalization (BPHE) (Rajavel, 2010), Adaptive Histogram Equalization (AHE) (Chang, 2018), Bi-Histogram Equalization (BHE) (Sengee, Sengee, & Choi, 2010) and Multi-Histogram Equalization (MHE) (Tan, & Isa, 2019). And the parameter used for comparison includes Average Mean Brightness Error (AMBE), image contrast (IC) and Average Information Content (AIC). The mathematical expression used for evaluating these parameters is given below.

$$AMBE = z_1 - z_2 \tag{16}$$

In equation (16) z_1 represents the mean of input image and z_2 represents the mean of output image. The output image in the sense is referred to as contrast enhanced image.

$$IC = \{max\, x_1 - min x_1\} \tag{17}$$

In equation (17) x_1 represents the pixel value of input image.

$$AIC = Pdf(x_1) * log(pdf(x_1)) \tag{18}$$

In equation (18) $Pdf(x_1)$ represents the probability density function of the contrast enhanced image. Further AMBE is an error metric and it is lower for the proposed method when compared to conventional approaches. On the other hand the rest of the two metrics such as AIC and IC is greater for the proposed framework on comparison to existing. This comparison study is given in pictorial representation in the following section.

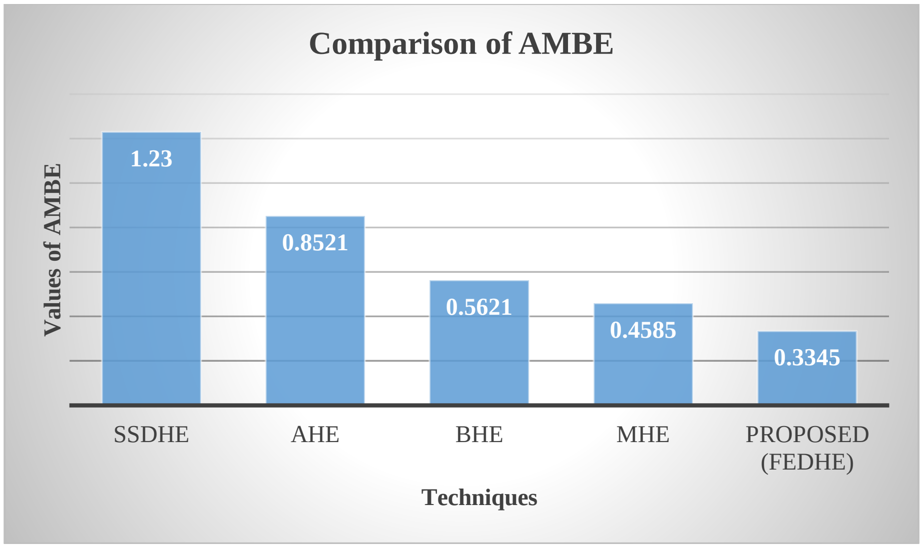


Figure 12 Comparison of average mean brightness error (AMBE)

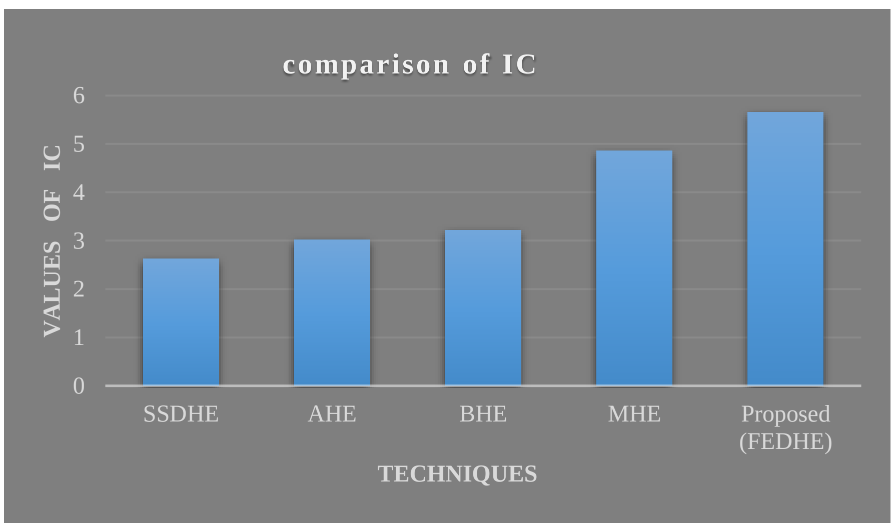


Figure 13 Comparison of image contrast

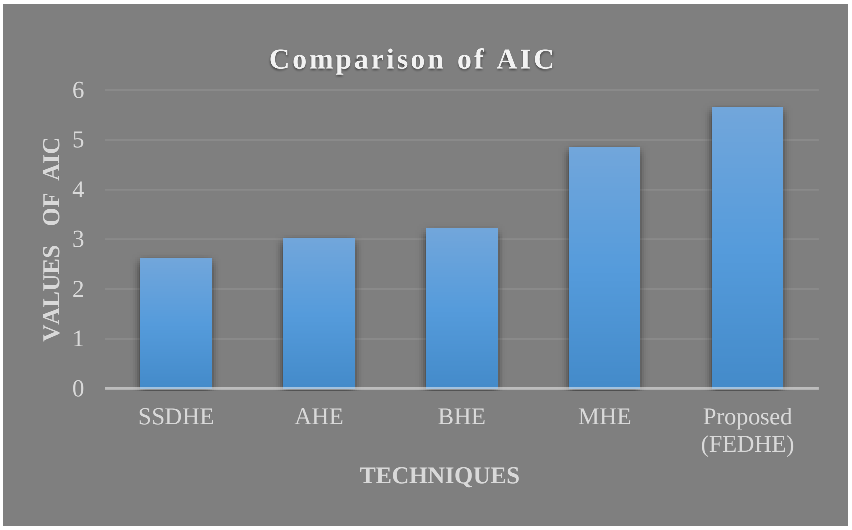


Figure 14 Comparison of average information content

The comparison of the AMBE metric is given in Figure 12. The value of AMBE for the proposed method is 0.3, and for the existing such as SSDHE, AHE, BHE and the MHE, the value is found to be 1.25, 0.85, 0.5 and 0.4. The comparison of IC metrics is given in Figure 13. The value of IC for the proposed method is 242, and for the existing methods such as SSDHE, AHE, BHE and the MHE, the values are 65, 85,122 and 175. The comparison of AIC is given in Figure 14. The value of AIC for the proposed method is 5.6, and for the existing approaches such as SSDHE, AHE, BHE and the MHE, the values are 2.6, 3.02, 3.2 and 4.8. Through comparison, the contrast enhancement technique used in this proposed framework functions better in comparison with other existing contrast enhancement approaches. In addition, the functioning of the proposed registration technique is compared with the conventional registration method based on execution time. The total time taken for the completion of the entire process is referred to as execution time.

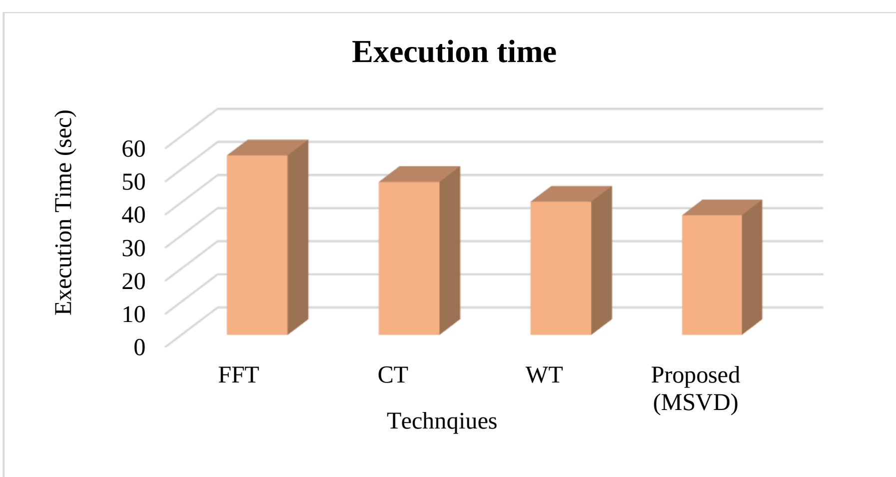


Figure 15 Comparison of execution time

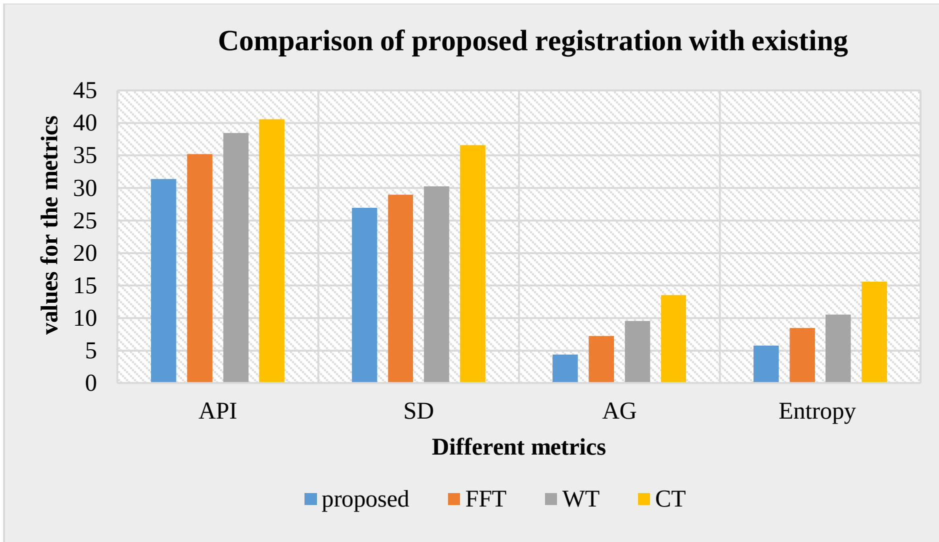


Figure 16 Comparison of proposed registration technique with existing contrast enhancement technique

The execution time calculated for the proposed process is compared with the conventional approaches. The conventional approaches used for comparison includes Fast Fourier Transform (FFT), Wavelet Transform (WT) and Contour Transform (CT). The comparison study of execution time is illustrated in graphical format, and it is given in Figure 15. The execution time for the proposed method is 36.14 sec, and for the conventional approaches such as WT, CT and FFT, the execution time was found to be 40.23 sec, 46.21 sec and 54.23 sec. In Figure 16, the comparison carried out between proposed and existing registration techniques with the help of various metrics is illustrated. The values for the metric such as API, SD, entropy and AG is lower for the proposed registration technique coupled with contrast enhancement. The comparison analysis performed between proposed and recent existing techniques is given in Table 3.

Table 3 Comparison between proposed and existing contrast enhancement techniques

Authors	**Techniques**	**AMBE**	**PSNR**	**Contrast**	**Entropy**
Kandhway, Bhandari, and Singh, (2020)	ATSHE	0.625	24.89	16.56	2.56
Mayathevar et al. [35]	FCHE	1.72	28.35	18.56	3.54
Saravanan and Karthigaivel (2021)	FSDHE	3.21	32.30	20.48	3.86
Proposed	(FEDHE)	0.3345	35.68	23.56	4.23

Table 3 illustrate the Comparison of AMBE between Proposed and Existing Contrast Enhancement Techniques. The proposed model attained less AMBE values than other methods. The existing methods such as, Adaptive Thresholding Based Sub-Histogram Equalization (ATSHE) attained 0.625 of AMBE, Fuzzy Color Histogram Equalization (FCHE) attained 1.72 of AMBE and Fuzzy and Spline based Dynamic Histogram Equalization (FSDHE) attained 3.21 of AMBE. This comparison shows that the proposed registration method coupled with contrast enhancement had attained excellent outcomes in comparison with existing registration approaches. This proves the effectiveness of the proposed framework. Finally, the overall analysis showed the superiority of the proposed registration technique in comparison with existing approaches.

5. Conclusion

This paper elaborates on the merging of contrast enhancement techniques along with registration. Generally, the process of registration in images is performed to join two images captured from different devices. However, the registered image lack in maintaining the information and quality of the image. To improve the quality of registered images, a contrast enhancement technique, namely FEDHE, is utilized. The histogram plot obtained for the image is equalized by employing the fuzzy rule to reach enhanced contrast. The contrast-enhanced image is further sent for the registration process using MSVD. The final outcome obtained through this proposed framework is a registered image with better quality. Then, the experimental analysis of the proposed architecture is carried out in two circumstances. One is registration with contrast enhancement, and another one is registration without contrast enhancement. The images subjected to registration with contrast-enhanced showed better results. Finally, the comparison analysis showed that the functioning of the proposed framework outperforms the existing one. Proposed contrast enhancement based registration technique is designed mainly focusing on medical images. In future this proposed technique can be applied in other optical images to enhance their quality.

6. Declarations

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Conflict of Interest

There is no conflict of Interest between the authors regarding the manuscript preparation and submission.

Data availability statement

There is no availability of data or materials available or report for the manuscript.

Code availability

No code is available for this manuscript**.**

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