An Efficient Brain MRI Image Downsampling Technique using Radon Transform and Genetic Algorithm

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Abstract: The Image compression is improved by decreasing the image before the encryption process and evaluating the missing area after decoding at lower bit rates. First the input RGB Brain MRI image is modified to gray scale Image. In our proposed approach, the input MRI image is pre-processed to reduce the image as down sampling image. Radon Transform is then applied for the image and then background is reduced by using soft threshold. Thereafter, to find the smooth threshold values of the image using genetic algorithm, then Image size is removed using Euclidean distance of similar blocks. This provides a sample output under a given input MRI image. This approach has showed good PSNR improvement compare with existing techniques. Finally this approach gives at higher bitrates.

Keywords: Downsampling, Radon Transform, Genetic Algorithm, Soft Thresholding.

1. INTRODUCTION

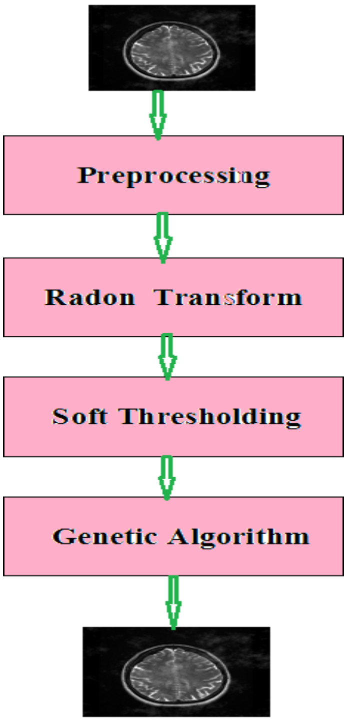
The visual signals are encoded by the low bit rates in Internet and mobile multimedia applications. Typical image compression methods (e.g., JPEG and JPEG2000 standards) attempt to assign available bits to the image. As the compression rate increases, the use of larger measurement step sizes results in reduced pixel bits (ppb), resulting in deterioration of the encoded image quality.

In [1], Zeng and Venetsanopoulos used a 2 × 2 average operator for spatial extinction before JPEG compression; In decoding, they used a replica filter and then a 5 × 5 Gaussian filter to retrieve the entire image. Brookstein et al. Exploited the theoretical model of reduction and compared it to experimental results. In the work of Psych et al, image-based extinction and interpolation filters are obtained for the image of Bruck-Stein et al., Resulting in filter parameters being sent to the decoder for better reconstruction. In existing projects, the reduction rate is preset by the users; In the case of variable bit-rate (VPR) application for different images, a coding process should switch between a minimization scheme and a traditional program if the critical bit rate is low and image dependent and good coding quality is sought.

In low bit-rate code, how an image is underestimated must be determined by the contents of the visual signal so that scarce bits can be used to achieve better coding quality. In light of this idea, we propose strategies to embrace the appropriate reduction rate / direction and measurement step for encoding each macro block in an image, based on the local visual significance of the signal. If possible, reduction in the direction of more spatial variations

2. PROPOSED WORK

Compression standards JPEG, MPEG, H.26x exposure serves many consumers and commercial multimedia applications, including multimedia content spread in its abbreviated form. A more efficient image of modelling model was proposed in this paper. Here we used the sample of the images below using DWT. Our proposed approach consists of four functions as an input image model.Fig. 1 shows the proposed flow of the down sampling technique.



The four levels of our proposed approach are given below:-

- Preprocessing
- Radon Transform
- Soft Thresholding
- Genetic Algorithm

In our proposed approach, the input image is prepared to prepare for the model below. Then use the DVD for the image, then apply the soft threshold to reduce the background. After that, genetic algorithm is detected in the soft intensity values of the film, using the Euclidean distance to remove the size of the film to remove similar blocks. This gives the sample output of the given input image.

3. Preprocessing

The input image here is modified from RGB to Gray scale image. The modified image is then given to the motion filter input to reduce motion content in the picture. The filtered filename was split into small blocks.

4. Radon Transform

The Radon Transform is used in computer Tomography and MRI to reconstruct the original shape. Radon Transform of f(x,y) is the line integral of parallel to y axis.

$$R_o (x^1) = \int_{-\infty}^{\infty} f(x' cos\theta - y' \sin\theta, x' sin\theta + y' cos\theta)\, dy'$$

Where

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} cos\theta & sin\theta \\ sin\theta & cos\theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

It is also possible to generalize the Radon transform still further by integrating instead over *k*-dimensional affine subspaces of R^n. The X-ray transformis the most widely used special case of this construction, and is obtained by integrating over straight lines.

5. Soft Thresholding

After using Radon Transform for all compilers in the image, soft Thresholding is used to reduce the background in the image, so VoXels are reduced with extreme values below the initial value (set to zero or set to zero). During the visualization, these gates become more transparent. If the original value S_i of a voxel is $S_i > (threshold\ value + range/2)$ then the final filtered value D_i does not change $(D_i = S_i)$. If $S_i < (threshold\ value - range/2)$ then the voxel is deleted $(D_i = 0)$For the values in between, a smooth function is applied: if $(threshold\ value - range/2) < S_i < (threshold\ value + range/2)$ then $D_i = f(S_i)$ according to the shape function, which in the case of the FastMip renderer, for instance, is a sinusoidal.

$$D_i = \begin{cases} 0 & If\ S_i < threshold - \frac{range}{2} \\ f(S_i) & If\ threshold - \frac{range}{2} \le S_i < threshold + \frac{range}{2} \\ S_i & If\ S_i \ge threshold + \frac{range}{2} \end{cases} \qquad (1)$$

During the study can be used on a soft door, for example cross-coefficients in a joint-analytical analyser. These cutting coefficients are based on binary images, where intensity voices at the bottom of the vault are set to zero, and the intersections above the gateway are calculated for volumes. To avoid sharp transitions, this image is not a valid binary (0 or 1) but greyscale, the median values of the pixels, the intensity of a certain range around the gateways.

6. Genetic Algorithm (GA)

After using a soft gap with all the pieces of the film, GA [14] is used to detect the number of nodes and the threshold value.In this method, the chromosome *A* is encoded as a binary string of the same size L^r of the reduced histogram, such that $A = a_0, a_1, a_2, a_3, \ldots\ldots, a^r_{L-1}$, where the character a_i is equal to 0 or 1. Where a_i indicates the peak or valley of the histogram. If $a_i = 0$, then the position i indicates the value of the threshold. Hence the number of zeros-bits occurred in A indicates number of thresholds.The fitness $F(k)$ for an image has defined as follows

$$F(k) = \rho * (Disk(k))^{1/2} + (\log_2(k))^2 \qquad (2)$$

Here $Disk(k)$ represents the within-class variance

$$Disk(k) = \sigma_w^2(k) = \sigma_T^2 - \sigma_B^2(k) \qquad (3)$$

The first term of $F(k)$ measures the cost incurred by the discrepancy between the thresholded image and the original image. The second term measures the cost resulted from the number of bits used to represent the thresholded image. In this equation, ρ is a positive weighting constant.

The $(k-1)$number of thresholds is determined by counting the number of zero-bits in the string and the threshold values are determined by the positions occupied by these zero-bits in the string. The function $F(k)$has a unique minimum, which is an important advantage. The optimum class number $k*$ and the $(k*-1)$best thresholds can be determined by the following equation:

$$F(k*) = \min\{F(k)\} \qquad (4)$$

The genetic algorithm starts with a randomly generated population of solutions. The initial population is of fixed size $P : A_1, A_2, \ldots A_P$. For each string i in the population $(i = 1,2,3,\ldots P)$, L^r bits (0 or 1) are randomly generated. The current population evolves to the next population of the same size using three standard genetic operations: selection, crossover and mutation. The evolution process is iterated until a specified number of generations are reached.

Choosing is akin to the natural survival of bile organisms. Each string is an exercise value derived by exercise evaluation. The probability of each selected string is a proportion of its exercise value.

In this paper, the tournament selection procedure is performed as follows: two strings A' and A'' of the current populations are randomly selected and the string with the best fitness value is chosen to belong to the mating pol. This procedure is repeated, until filling a mating pool of the same size P that the population.

The crossover operator chooses two strings A' and A'' of the current population. Single crossover is applied as follows: generate a random integer number q within $[0, L^r - 1]$and create two offspring by swapping all the characters of A' and A'' after position q. The crossover is performed with the crossover probability P_c. A random number can be generated within [0, 1], associated with each pair of strings selected in the mating pool. If the random value is less than P_c, then the crossover is performed, otherwise no crossover is performed.

Mutation is an occasional alteration of a character with a low probability P_m. The proposed mutation is performed in two steps. First, a standard mutation is used in the following way: for each string produced by crossover operation, a random value is generated within [0, 1]. If the random number is less than P_m, then a character at a random position is chosen and its value is altered (i.e. one changes 0 to 1, or 1 to 0). However, the crossover and standard mutation operators can create strings with several successive zero-bits. In this situation, several thresholds with successive values appear. To overcome this undesirable situation, a solution consists in keeping, among successive zero-bits, only the first one, and in mutating the remaining successive zero-bits.

Because of the reduced dimension of the histogram, the threshold values t_i determined by the GA are at lower level, i.e. $t_i \in [0\ L]$. Thus, the thresholds determined by the GA must be expanded in the original space. In this case, each threshold t_i is multiplied by a factor 2^r, as follows,

$$\hat{t}_i = t_i 2^r \text{, for } i = 1, \ldots k-1 \text{, such that } \hat{t}_i \in [0\ L] \quad (5)$$

After finding the entry value, each group is compared to other groups in the use of the distinctive method of Euclidean. This comparison helps you find a similar set to be removed for removal. Comparing all similar packages, after removal, the film's low output is obtained.

7. EVALUATION METRICS

The metrics used to evaluate the denoised images are called evaluation metrics. It is of various types:

7.1 MSE (Mean Square Error)

It measures the average of the squares of the "errors". The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate. The MSE is the second moment of the error. For an unbiased estimator, the MSE is the variance. MSE has the same units of measurement as the square if the quantity being estimated. For an unbiased estimator, the RMSE is the square root of the variance, known as the standard deviation.

The equation for mean square error is given by

$$MSE = \frac{1}{MN} \sum_{j=1}^{M} \sum_{k=1}^{N} (x_{j,k} - x'_{j,k})^2 (1)$$

Where,

$x_{j,k}$ is the original image and

$x'_{j,k}$ is the denoised image

7.2 PSNR (Peak Signal to Noise Ratio)

It is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. PSNRs usage is most commonly found to measure the quality of reconstruction of lossy compression codes like for image compression. In this case, the signal is the original data and the noise is the error introduced by the compression. PSNR is an approximation to human perception of reconstruction quality. A higher PSNR generally indicates that the reconstruction is of higher quality. PSNR is only conclusively valid when it is used to compare results from the same code and content.

PSNR is most easily defined via MSE (Mean Squared Error). PSNR is most easily defined via the MSE. Given a noise-free M×N monochrome image $x_{j,k}$ and the denoised image $x'_{j,k}$, PSNR is defined as,

$$PSNR = 10log\frac{(255)\char`^2}{MSE} \qquad (2)$$

Where,

$x_{j,k}$ is the original image and

$x'_{j,k}$ is the denoised image.

The formula for normalized absolute error (NAE) is given by,

$$\mathrm{NAE} = \sum_{j=1}^{M}\sum_{k=1}^{N}\left|x_{j,k} - x'_{j,k}\right| / \sum_{j=1}^{M}\sum_{k=1}^{N}\left|x_{j,k}\right|$$

Where,

$x_{j,k}$ is the original image and

$x'_{j,k}$ is the denoised image.

7.3 Normalized Absolute Error:

The formula for Normalized Absolute Error (NAE) is given by,

$$\mathrm{NAE} = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N}\left|x_{j,k} - x^{!}{}_{j,k}\right|}{\sum_{j=1}^{M}\sum_{k=1}^{N}\left|x_{j,k}\right|}$$

Where,

$x_{j,k}$ is the original image

$x^{!}{}_{j,k}$ is the denoised image

8. RESULTS AND DISCUSSION

In this section we can find the results and discussion of the proposed method. Our proposed image is used for reducing the method and given the results of various images analyzed and derived in this section.

Initially the input image is converted to gray scale image for convenient functionality from the RGB size. The modified gray scale image is then filtered using the motion filter to remove the contents of the image in the image. After filtration is applied, the small size images should be separated, follow the downsampling technique. The sample image after segmentation is shown in Fig.2. Then Radon Transform is applied to the segmented input image.

Then soft thresholding is applied to the output image and then GA is applied to get the clear downsampled image. Fig. shows the output of the proposed method for several input images.

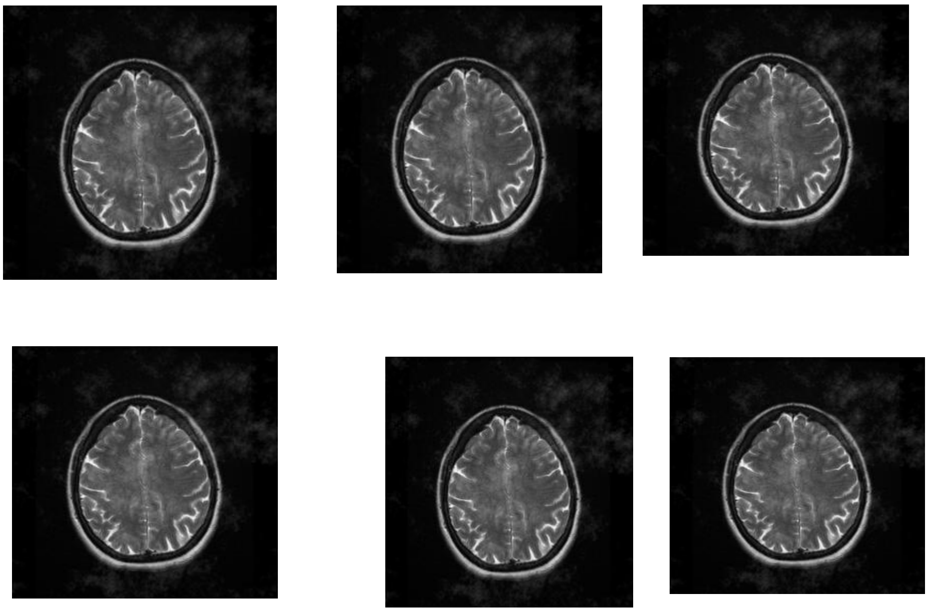


Fig. 4 (a) Input image and (b) Radon Transforms Quantization output image

Figure 1-Simulation results for existing and proposed method

Table 1- Comparison of all techniques

Techniques	PSNR (dB)	MSE	Time Elapsed in seconds	Normalized Absolute Error
Wavelet Transform	58.56	384.64	8.24	15.87
Curvelet Transform	77.62	263.41	7.23	9.653
Contourlet Transform	84.31	156.44	8.35	7.596
Wavelet Thresholding	46.51	763.28	4.35	5.353
Modified Wavelet Thresholding	51.72	685.44	2.88	1.023
Genetic Algorithm	56.64	564.34	9.55	28.06
Genetic and	93.24	8.525	1.58	0.006

Curvelet Transform				
Proposed Combination of Genetic and Radom Transform	94.37	8.411	1.47	0.0024

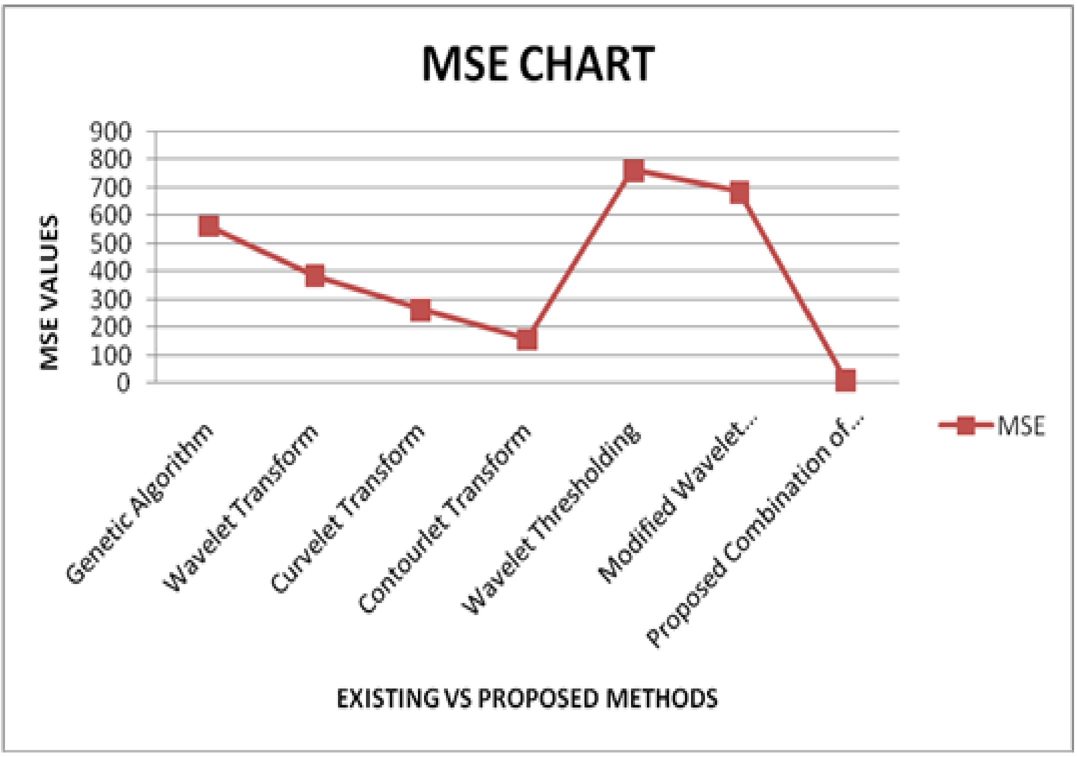


Figure 2-Mean Square Error (MSE) graph for different Techniques

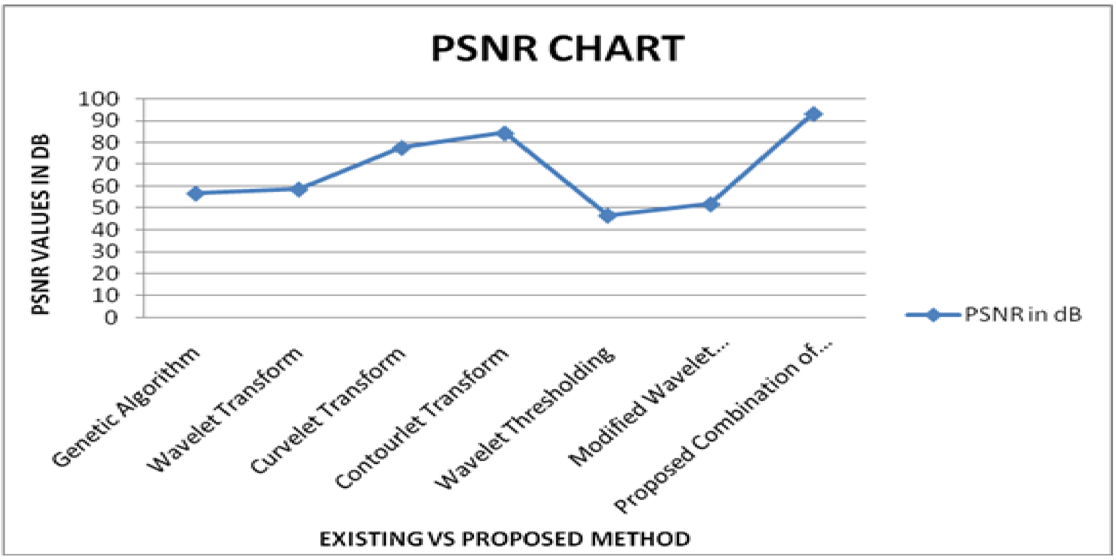


Figure 3-Peak Signal to Noise Ratio (PSNR) Value Chart for different Techniques.

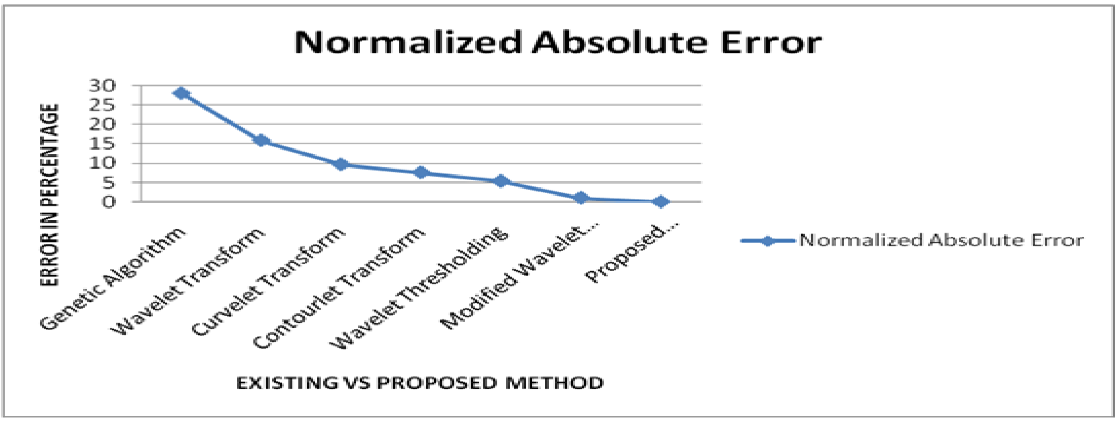


Figure 4-Different Methods of Normalized Absolute Error .

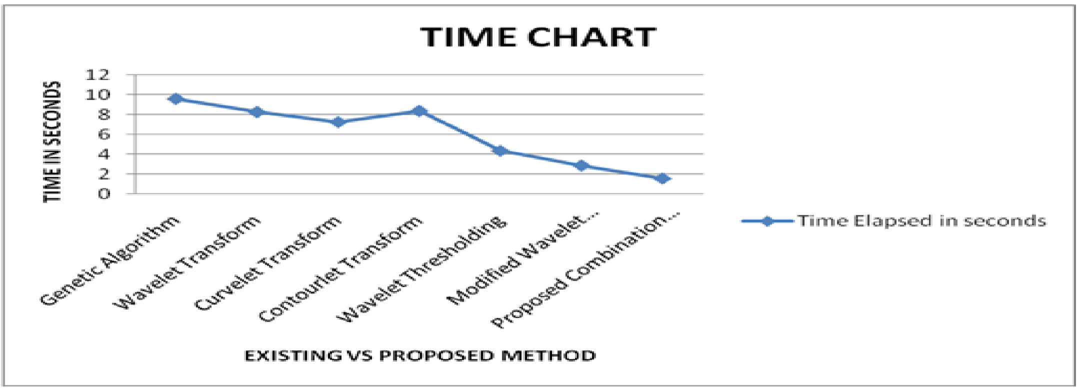


Figure 5- Chart for different methods Of Elapsed Time

CONCLUSION

Therefore, many methods can be used to reduce the sample size and down sampling are implemented in the wavelet domain. The comparison of these different methods is difficult because any method can be used by changing the comparison criterion. By checking theoretically or statistically a number of properties that fully characterize fractional images, the comparison was made. The proposed combination of Radon Transform and Genetic algorithm has been found to be superior to other techniques in terms of high PSNR, low MSE, low NAE and Low elapsed time.

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