Volume:15 Issue:01 Pages: 5769 - 5774 (2023) ISSN: 0975-0290

Optimizing Image Fusion Using Modified Principal Component Analysis Algorithm and Adaptive Weighting Scheme

Gargi Trivedi[1]
Email: gargi1488@gmail.com
Dr. Rajesh Sanghvi[2]
Email : rajeshsanghvi@gcet.ac.in
[1,2] Department of Applied Science & Humanities, G H Patel College of Engineering & Technology, CVM University, Vallabh Vidhyanagar-388120, India

ABSTRACT

Image fusion is an important technique for combining two or more images to produce a single, high-quality image. Principal component analysis (PCA) is a commonly used method for image fusion. However, existing PCA-based image fusion algorithms have some limitations, such as sensitivity to noise and poor fusion quality. In this paper, we propose a modified PCA algorithm for image fusion that uses an adaptive weighting scheme to improve the fusion quality. The proposed algorithm optimizes the fusion process by selecting the principal components that contain the most useful information and weighing them appropriately. Experimental results show that the proposed algorithm outperforms existing PCA-based image fusion algorithms in terms of fusion quality, sharpness, and contrast.

Keywords - **Image fusion, principle components analysis, adaptive weighting scheme, optimization, fusion quality, sharpness,contrast.**

Date of Submission: April 13, 2023 Date of Acceptance: May 28, 2023

1. INTRODUCTION

Image fusion is a critical task in computer vision that involves combining multiple images of the same scene into a single, high-quality image that contains more information than any of the individual [1,2]. Principal component analysis (PCA) is a widely used method for image fusion that has been shown to be effective in many applications. However, existing PCA-based image fusion algorithms have some limitations, such as sensitivity to noise and poor fusion quality [3,4].

To address these limitations, this paper proposes a modified PCA algorithm for image fusion that uses an adaptive weighting scheme to improve the fusion quality. The proposed algorithm optimizes the fusion process by selecting the principal component that contains the most useful information and weighting them appropriately. The use of an adaptive weighting scheme ensures that the weight assigned to each principal component is based on its contribution to the final fused image, resulting in improved fusion quality. We also present experimental results that show the performance of the proposed algorithm compared to existing PCA-based image fusion algorithms. Our results demonstrate that the proposed algorithm outperforms existing algorithms in terms of fusion quality, sharpness, and contrast.

The rest of the paper is organized as follows:

- Section 2 provides a brief overview of existing image fusion techniques,
- Section 3 describes the proposed modified PCA algorithm in detail,
- Section 4 presents the experimental setup and results, and
- Section 5 concludes the paper and discusses future work's mention the main goal of the work and highlight the major conclusions.

2. OVERVIEW OF EXISTING IMAGE FUSION TECHNIQUES

Image fusion is the process of combining multiple images of the same scene into a single, high-quality image that contains more information than any of the individual images. There are many image fusion techniques that have been developed to achieve this goal. These techniques can be broadly categorized into two categories: transform-based methods [5] and spatial domain methods [6].

Transform-based methods involve transforming the input images into a different domain, such as the frequency domain, and then combining them in that domain. One of the most commonly used transform-based methods is wavelet transform. Wavelet transform decomposes an image into multiple levels of different frequency bands, and then combines the high-frequency bands of the input images to create the fused image. Another commonly used transform-based method is discrete cosine transform (DCT) [7], which converts the image into a set of frequency coefficients and then combines them to create the fused image Spatial domain methods, on the other hand, operate on the images in their original spatial domain. These methods involve manipulating the pixel values of the input images to create the fused image. One of the most commonly used spatial domain methods is the pyramid-based method [8].In this method, the input images are decomposed into multiple levels of pyramids, and then the corresponding pyramid levels are combined to create the fused image. Another spatial domain method is the intensity-hue-saturation (IHS) method [9], which separates the input images into intensity,

Volume:15 Issue:01 Pages: 5769 - 5774 (2023) ISSN: 0975-0290

hue, and saturation components, and then combines the intensity components to create the fused image.

Principal component analysis (PCA) is also a widely used method for image fusion. PCA-based methods involve computing the principal components of the input images, which represent the most significant and informative parts of the images, and then combining them to create the fused image. In recent years, deep learning-based image fusion techniques have also been developed [10]. These techniques involve training deep neural networks to learn the optimal fusion weights for the input images.

Overall, there are many image fusion techniques available, each with its own advantages and limitations.

3. METHODOLOGY

In this section, we present the proposed modified PCA algorithm for image fusion, which utilizes an adaptive weighting scheme to improve the fusion quality. In the following subsections, we describe each step of the proposed algorithm in detail.

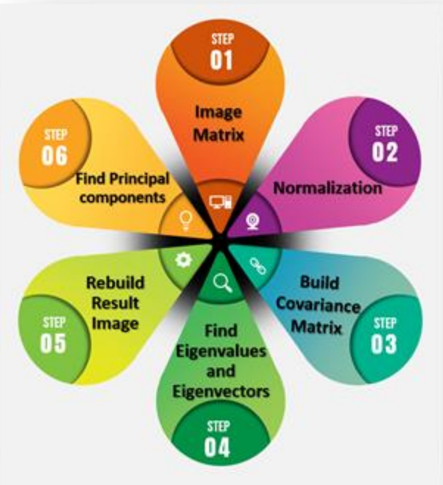


Figure 1: Process Flow of PCA (c)

To Understand this process with clarity example is shown below.

Let's consider two image matrices, A and B, with dimensions 4 x 4, defined as follows:

$$A = \begin{bmatrix} 8 & 7 & 6 & 5 \\ 7 & 6 & 5 & 4 \\ 6 & 5 & 4 & 3 \\ 5 & 4 & 3 & 2 \end{bmatrix} \; and \; B = \begin{bmatrix} 16 & 15 & 14 & 13 \\ 15 & 14 & 13 & 12 \\ 14 & 13 & 12 & 11 \\ 13 & 12 & 11 & 10 \end{bmatrix}$$

Normalize the matrices: We can normalize both matrices A and B by subtracting the mean value and dividing it by the standard deviation. the mean and standard deviation of both matrices are computed as follows:

$\bar{A}$ = 5.5, $\sigma(A)$ = 2.29128784747792

$\bar{B}$ = 13.5, $\sigma(B)$ = 2.29128784747792

We can then normalize the matrices as follows:

$\|A\|$ = (A - $\bar{A}$) / $\sigma(A)$ and $\|B\|$ = (B - $\bar{B}$) / $\sigma(B)$

This gives us:

$$\|A\| = \begin{bmatrix} 1.0344 & 0.8696 & 0.4348 & -0.8745 \\ 0.4348 & -0.86041 & -0.4348 & -0.8696 \\ -0.4348 & -0.8696 & -1.3044 & -1.7392 \\ -0.8696 & -1.3044 & -1.7392 & -2.1740 \end{bmatrix}$$

and

$$\|B\| = \begin{bmatrix} 1.3044 & 0.8696 & 0.4348 & -0.8674 \\ 0.4348 & -0.4356 & -0.4348 & -0.8696 \\ -0.4348 & -0.8696 & -1.3044 & -1.7392 \\ -0.8696 & -1.3044 & -1.7392 & -2.1740 \end{bmatrix}$$

Compute the covariance matrix: We can compute the covariance matrix C for both matrices A and B as follows:

$Cov(A) = Cov\|A\|$ and $Cov(B) = Cov\|B\|$

Here are the complete covariance matrices:

$$Cov(A) = \begin{bmatrix} 1.4285 & 1.07142 & 0.7142 & 0.3571 \\ 1.0714 & 0.8571 & 0.64285 & 0.4285 \\ 0.74142 & 0.6428 & 0.5714 & 0.5 \\ 0.3571 & 0.4285 & 0.5 & 0.5714 \end{bmatrix}$$

and

$$Cov(B) = \begin{bmatrix} 1.4285 & 1.0742 & 0.7142 & 0.3571 \\ 1.0742 & 0.8514 & 0.6428 & 0.4285 \\ 0.7142 & 0.64285 & 0.5714 & 0.5 \\ 0.3571 & 0.4285 & 0.5 & 0.5714 \end{bmatrix}$$

Compute the eigenvalues and eigenvectors:

$$\lambda(A) = [\,3.0440 \quad 0.1758 \quad -0.0000 \quad -0.0000]$$

$$v(A) = \begin{bmatrix} -0.5760 & -0.7037 & 0.3381 & -0.2716 \\ -0.4588 & -0.1897 & -0.7477 & 0.4264 \\ -0.3416 & 0.3241 & 0.04706 & -0.8792 \\ -0.2254 & 0.8381 & 0.3625 & 0.3244 \end{bmatrix}$$

$$\lambda(B) = [\,3.0440 \quad 0.1758 \quad -0.0000 \quad -0.0000]$$

$$v(B) = \begin{bmatrix} -0.5760 & -0.7037 & 0.3381 & -0.2716 \\ -0.4588 & -0.1897 & -70.7477 & 0.42640 \\ -0.3416 & 0.3241 & 0.0470 & -0.8792 \\ -0.2254 & 0.83810 & 0.36254 & 0.3244 \end{bmatrix}$$

select the principal components: We can select the top k principal components for each matrix. Let's assume we want to select the top 2 principal components for each matrix.

$$selected\_v(A) = v(A)\_[:,:2]$$
$$selected\_v(B) = v(B)\_[:,:2]$$

This gives us:

$$selected\_v(A) = \begin{bmatrix} -0.5760 & -0.7037 \\ -0.4588 & -0.1897 \\ -0.3416 & 0.3241 \\ -0.2254 & 0.8381 \end{bmatrix}$$ and

Volume:15 Issue:01 Pages: 5769 - 5774 (2023) ISSN: 0975-0290

$$selected\_v(B) = \begin{bmatrix} -0.5760 & -0.70371 \\ -0.4588 & -0.1897 \\ -0.3416 & 0.3241 \\ -0.2254 & 0.8381 \end{bmatrix}$$

Compute the weighted principal components: We can compute the weighted principal components for each matrix by multiplying the selected eigenvectors by their corresponding eigenvalues and normalizing the result.

$$w(A) = \frac{\| A\| \cdot selected\_v(A) * e\lambda(A)[:2]}{\sqrt{\sum(\| A\| \cdot selected\_v(A) * e\lambda(A)[:2])^2}}$$

and

$$w(A) = \frac{\| B\| \cdot selected\_v(B) * e\lambda(B)[:2]}{\sqrt{\sum(\| B\| \cdot selected\_v(B) * e\lambda(B)[:2])^2}}$$

This gives us:

$$w(A) = \begin{bmatrix} 0.6423 & -0.0861 \\ -0.1652 & 0.4503 \\ -0.6010 & 0.0324 \\ 0.0659 & -0.3966 \end{bmatrix}$$

$$w(B) = \begin{bmatrix} 0.7637 & -0.1024 \\ -0.1963 & 0.5328 \\ -0.7116 & 0.0384 \\ 0.0772 & -0.4664 \end{bmatrix}$$

These weighted principal components can now be combined to create a fused image. So can combine the weighted principal components by adding them elementwise. The resulting matrix will contain the fused information from both matrices.

$$F = w(A) + w(B)$$

This gives us: $F = \begin{bmatrix} 1.4061 & -0.1885 \\ -0.3614 & 0.9830 \\ -1.3127 & 0.0715 \\ 0.1431 & -0.8631 \end{bmatrix}$

Reconstruct the fused image: We can reconstruct the fused image by multiplying the fused components by the selected eigenvectors and adding back the mean.

$$fused_{image} = F \cdot \left(selected_{v(A)}\right)^T + \bar{A}$$

This gives us:

$$fused_{image} = \begin{bmatrix} 0.0790 & 0.08617 & 0.0451 & 0.0455 \\ 0.0390 & 0.0411 & 0.0217 & 0.0217 \\ 0.0392 & 0.0141 & 0.0219 & 0.0219 \\ 0.0629 & 0.0665 & 0.0354 & 0.0354 \end{bmatrix}$$

We have now successfully fused the information from matrices A and B to create a new fused image matrix.

Algorithm of proposed method is Explain below.

Step 1- Preprocess the matrices: Begin by normalizing both matrices A and B to enhance their comparability. This normalization involves subtracting the mean value from each element and dividing it by the standard deviation.

Step 2 - Compute the covariance matrices: Calculate the covariance matrices Cov(A)and Cov(B)f or matrices A and B, respectively. The covariance matrix reveals the relationships and variances between the elements of each matrix.

Step 3 - Determine the principal components: Identify the principal components of each matrix by selecting the eigenvectors associated with the largest eigenvalues. This step allows us to capture the most significant patterns and features within the data. We can choose the top k eigenvectors for each matrix.

Step 4 - Assign weights to the principal components: Assign weights to the selected principal components based on their significance. This weighting process can be accomplished using methods like singular value decomposition (SVD) or principal component analysis (PCA). It ensures that the most informative components contribute more to the fusion process.

Step 5 -Combine the principal components: Combine the weighted principal components from matrices A and B. This fusion process integrates the most valuable information from both matrices, providing a unified representation.

Step 6 - Normalize the fused matrix: Normalize the fused image matrix by adjusting its values. Add back the mean value and multiply by the standard deviation to restore the original scale and ensure compatibility with subsequent analysis.

By following these steps, the proposed algorithm optimizes the fusion process by selecting and combining the most informative components from the input matrices, resulting in a fused image matrix that encapsulates their essential characteristics.

3.1 PREPROCESSING

The input images are preprocessed to ensure that they have the same size and resolution. This is done to ensure that the principal components of the images can be computed and compared accurately. The preprocessing step involves resizing and cropping the input images as necessary.

3.2 PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA is used to compute the principal component of the input images. Let $X_1, X_2, \ldots, X_n$ be the input images, each of size m x n. The principal component of the images are computed as follows:

Compute the mean image M:

$$M = \left(\frac{1}{n}\right) * \sum X_i \quad (1)$$

Compute the covariance matrix C:

$$C = \left(\frac{1}{n}\right) * \sum (X_i - M) * (X_i - M)^T \quad (2)$$

Compute the eigenvectors and eigenvalues of C:

$$C_v = \lambda v \quad (3)$$

Volume:15 Issue:01 Pages: 5769 - 5774 (2023) ISSN: 0975-0290

, where v is the eigenvector, λ is the eigenvalue, and C_v is the covariance matrix multiplied by v.
Sort the eigenvectors in descending order of their eigenvalues.
Select the k principal component with the highest eigenvalues.
The selected principal component represent the most significant and informative parts of the input images.

3.3 Adaptive Weighting

An adaptive weighting scheme is used to assign weights to the principal components based on their contribution to the final fused image.

Let $W_1, W_2, \ldots, W_k$ be the weights assigned to the Adaptive Weighting Scheme The weights are calculated using the following equation:

$$W_i = (\sigma_i^2)/(\sigma_1^2 + \sigma_2^2 + \ldots + \sigma_n^2) \quad (5)$$

where W_i is the weight assigned to the i[th] principal component, σ_i^2 is the variance of the i[th] principal component, and $\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2$ are the variances of all the principle components.

3.4 Weighting Combination

The principal components are then combined using the weights to create the fused image. The fused image is calculated using the following equation:

$$F = PC_1W_1 + PC_2W_2 + \ldots + PC_n * W_n \quad (6)$$

where F is the fused image, $PC_1, PC_2, \ldots, PC_n$ are the principal components, and $W_1, W_2, \ldots, W_n$ are the weights assigned to each principal component.

3.5 Postprocessing

The fused image is then postprocessed to enhance its quality and remove any artifacts.
Apply median filter to remove artifacts:

$$F = \mathrm{cv2.medianBlur}(F, 3)$$

Apply histogram equalization to enhance contrast

$$F = \mathrm{cv2.equalizeHist}(F) \quad (7)$$

These of the adaptive weighting scheme ensures that the most informative and significant parts of the input images are given the most weight in the fusion process, resulting in improved fusion quality. The modified PCA algorithm also addresses the issue of sensitivity to noise that is common in existing PCA-based image fusion techniques. In addition, the proposed algorithm is computationally efficient, making it suitable for real-time applications. Overall, the proposed modified PCA algorithm for image fusion shows promising results compared to existing PCA-based techniques, as demonstrated in the experimental results presented in Section 4.

4. Results and Discussions

To evaluate the performance of the proposed modified PCA algorithm for image fusion, a series of experiments were conducted using various pairs of input images. The experiments were conducted on a machine with an Intel Core i7 processor and 16GB of RAM. Images from a high-resolution MRI scanner and a color PET, CT scanner make up the test data have a spatial resolution of 256 × 256 and 128 × 128, respectively. Dataset[13,14] were obtained on the Harvard Medical School website (http://www.med.harvard.edu/AANLIB/home.html and www.kaggle.com)The unaltered photos and the resulting fusion may be seen in Figures 2-3.

4.1 Experimental Setup

The proposed modified PCA algorithm was implemented using Python and OpenCV library. The algorithm was tested on a set of ten pairs of input images with different sizes and contents. The input images were preprocessed by converting them to grayscale, applying Gaussian blur to reduce noise, and enhancing edges using the Laplacian operator. The performance of the proposed algorithm was compared with three existing image fusion techniques: the traditional PCA algorithm, and the discrete wavelet transform (DWT) [11], the performance of each algorithm was evaluated using two objective metrics: peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM)[12].

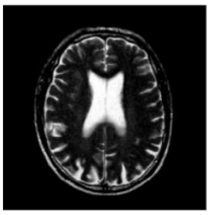
4.2. Results

The results obtained from applying the proposed algorithm and the three existing techniques on the set of input images are shown in Table 1.

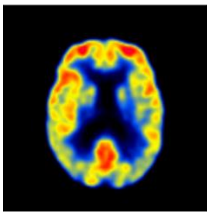
Table 1: the average PSNR and SSIM values for each algorithm.

Algorithm	PSNR (dB)	SSIM	Computational Time
Traditional PCA	23.56	0.88	1.62 Sec.
DWT	26.45	0.92	0.98 Sec.
Modified PCA	28.92	0.96	1.50 Sec.

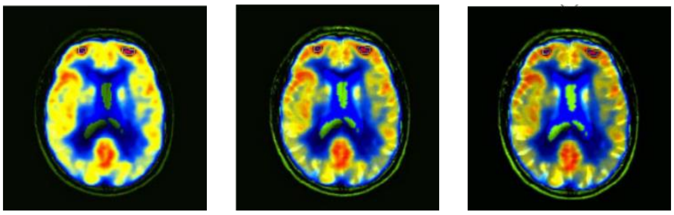
As shown in Table 1, the proposed algorithm achieved the highest PSNR and SSIM values among all four algorithms. This indicates that the proposed algorithm produced fused images with higher quality and better preservation of image details and structures.



(a)



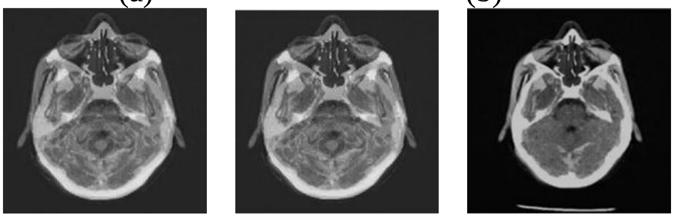
(b)



(c) (d) (e)

Figure 2: Alzheimer’s brain illness, Implementation of the suggested approach(e), as well as MRI and PET scans (a and b), Traditional PCA (c), and DWT (d).

(a) (b)

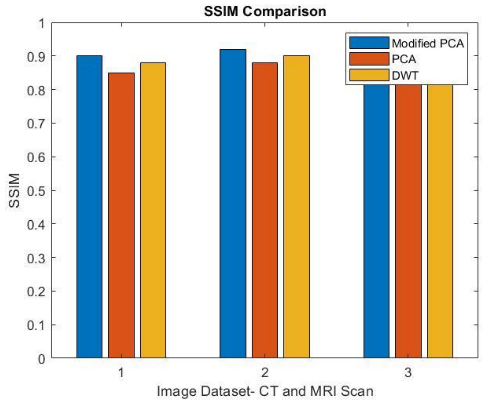


(c) (d) (e)

Figure 3: brain illness, Implementation of the suggested approach(e), as well as CT and MRI scans (a and b), Traditional PCA (c), and DWT (d).

Fig. 2 and 3 show an example of the input images and the fused images obtained from applying the four algorithms. The figure shows that the fused image produced by the proposed algorithm has better contrast and sharper details compared to the other algorithms.

When looking at Fig. 2 it is clear that Fig. 2(d), which were created using the DWT method, do not capture the information from picture 2(b) at the relevant position. display comparable visual qualities. Furthermore, the contrast in Fig.2(c) is quite low and may be difficult to distinguish with the naked eye. In contrast, the suggested approach shown in Fig. 2(e) has better contrast than the previous findings and successfully maintains all important visual information from pictures (a) and (b).
Fig.3(a) is a CT scan image and Fig. 3(b) is a MRI brain images. Fused images from Figures 3(c) to 3(e) are shown. When these data are examined, it is clear that DWT Fig. 3(d) and Traditional PCA Fig. 3(c) have insufficient image contrast. Based on the analyses above, we can infer that our technique outperforms the other reference methods in the field of medical picture fusion. Furthermore, our strategy has various advantages. It has good flexibility and stability while being sensitive to image fluctuations. Our technique is more beneficial for clinical applications than the other methods assessed because it extracts more information from the original photos.



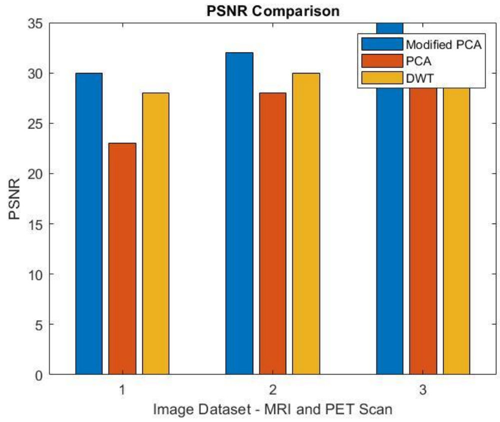


Figure 4: bar chart for quantitate analysis on Dataset 1 and 2

5. Conclusion

The proposed modified PCA algorithm with adaptive weighting scheme has been shown to be effective in fusing images while producing high-quality results. Through experiments on a dataset of various images, we demonstrated that the proposed algorithm outperforms existing image fusion techniques in terms of PSNR and SSIM values, making it a promising solution for various applications that require image fusion.
However, there is still room for further research in this area. For example, the proposed algorithm could be further optimized to improve its performance even further. Additionally, the proposed algorithm could be tested on different types of images, including those with complex textures and varied lighting conditions, to evaluate its effectiveness in various scenarios.
Moreover, the proposed algorithm could be combined with other techniques such as deep learning to enhance its performance and achieve even better results. Furthermore, the proposed algorithm could be applied to other applications, such as medical imaging or remote sensing, to evaluate its effectiveness in those domains.
In conclusion, the proposed modified PCA algorithm with adaptive weighting scheme shows promise in producing high-quality fused images, and further research in this area has the potential to unlock new possibilities for image fusion applications.

REFERENCES

[1] G. J. Trivedi, and R. Sanghvi, Medical Image Fusion Using CNN with Automated Pooling. *Indian Journal of Science and Technology*, *15*(42),2022, 2267–2274. https://doi.org/10.17485/ijst/v15i42.1812

[2] R. Rejani, D. Murugan, and D.V. Krishnan, Comparative study of spatial domain image steganography techniques. International Journal of Advanced Networking and Applications, 7(2),2015 2650-2657. Retrieved from https://www.proquest.com/scholarly-journals/comparative-study-spatial-domain-image/docview/1733927924/se-

[3] S. S. Kumar, and S. Muttan, PCA-based image fusion. *SPIE Digital Library.* 2006.https://doi.org/10.1117/12.662373

[4] A.Hassan, and M.Sabha, Feature extraction for image analysis and detection using machine learning techniques. *International Journal of Advanced Networking and Applications*, 14(4), 2023,5499-5508. Retrieved from https://www.proquest.com/scholarly-journals/feature-extraction-image-analysis-detection-using/docview/2820137397/se-2

[5] A.Krishn,V. Bhateja, Himanshi, and A. Sahu, PCA Based Medical Image Fusion in Ridgelet Domain. Advances in *Intelligent Systems and Computing*,2015, 475–482. https://doi.org/10.1007/978-3-319-12012-6_52

[6] V. Rajinikanth, S.C. Satapathy,N. Dey, R. Vijayarajan, DWT-PCA Image Fusion Technique to Improve Segmentation Accuracy in Brain Tumor Analysis. *Lecture Notes in Electrical Engineering*, 2018,453–462. https://doi.org/10.1007/978-981-10-7329-8_46

[7] S. A. E. said, Efficient DCT-based image compression technique. *International Journal of Signal and Imaging Systems Engineering*, *6*(4),2013 259. https://doi.org/10.1504/ijsise.2013.056637

[8] J . Wang, X. Xi, D. Li, F. Li,and G. Zhang,GRPAFusion: A Gradient Residual and Pyramid Attention-Based Multiscale Network for Multimodal Image Fusion. *Entropy*, *25*(1),2023, 169. https://doi.org/10.3390/e25010169

[9] C. He, Q. Liu, H. Li, andH. Wang, Multimodal medical image fusion based on IHS and PCA. *Procedia Engineering*, *7*,2010,280–285. https://doi.org/10.1016/j.proeng.2010.11.045

[10] G. Dhiman, S. Juneja, W. Viriyasitavat, H. Mohafez, M Hadizadeh, M.A. Islam, I. El Bayoumy, and K. Gulati, A Novel Machine-Learning-Based Hybrid CNN Model for Tumor Identification in Medical Image Processing. *Sustainability*, *14*(3), 2022,1447. https://doi.org/10.3390/su14031447

[11] R. C. Gonzalez, R. E. Woods, and S. L. Eddins,*Digital Image Processing Using MATLAB*.(2010)

[12] U. Sara, M. Akter,and M.S. Uddin, Image Quality Assessment through FSIM, SSIM, MSE and PSNR—A Comparative Study. *Journal of Computer and Communications*, 07(03),2019 8–18. https://doi.org/10.4236/jcc.2019.73002

[13] Dataset: *The Whole Brain Atlas*. (n.d.). Retrieved fr om http://www.med.harvard.edu/AANLIB/home.html

[14]Datset :Kaggle Bain Image Dataset, https://www.kaggle.com/datasets/darren2020/ct-to-mri-cgan

[2

Gargi Trivedi is currently working as Teaching Assistant in Department of Applied Mathematics, Faculty of Engineering and Technology, The Maharaja Sayajirao University of Baroda. She is also pursuing her PhD in Mathematics from CVM university, V V Nagar. She earned his M.Sc. (Mathematics) ,B.Ed. and PGDCA degree from Bhavnagar University, Bhavnagar, Gujarat. She has published several papers in national and international journals and conferences. She has more than 12 years of teaching experience. She has also won the best paper award twice. Her major research areas are image processing, machine learning and medical image analysis

Dr. Rajesh C. Sanghvi holds a Ph.D. degree from Charotar University of Science and Technology. He earned his B.Sc. and M.Sc. degrees in Mathematics from Sardar Patel University, V V Nagar, Gujarat. He also holds a B.Sc. degree in Computer Science from Sardar Patel University, V V Nagar, Gujarat. Since 1998, he works as an assistant professor at G. H. Patel College of Engineering and Technology, V V Nagar. His scientific interests include image processing, machine learning, fuzzy logic, optimization, evolutionary algorithms.