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Medical images fusion using two-stage combined model DWT and DCT

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ABSTRACT

The purpose of image enhancement is to improve the interpretation or perception of information in the image for viewers and the input of automated processing systems. Combining a multicenter image is a way of combining several images on a screen, focusing on different objects so that all objects appear in focus in the final image. Wavelet transform and cosine transform are used in many image processing applications, including image fusion. This paper's technique will combine DWT and DCT in two steps for medical MRI and PET images, eventually extracting the combined image. Input images are first divided into 8-pixel blocks in which DCT coefficients are extracted. After extracting the DCT coefficients, the first step of the combination takes place. The re-images will then be combined with the DWT conversion. According to the presented data, the proposed method achieved up to 5% better combination and, as a result, better image quality than the single-stage DWT and DCT methods.

1. Introduction

Image processing is now more commonly referred to as digital image processing. It is a computer science branch that deals with digital signal processing, representing images taken with a digital camera or scanned by a scanner. Image processing has two main branches: improving image and machine vision. Improving images includes blurring filters and increasing contrast to improve the visual quality of images and ensure that they are displayed correctly in the destination environment (such as printers or computer monitors). In contrast, machine vision uses methods that help them. And understanding the content of images to be used in works such as robotics and keratoconus detection [1, 2]. In a specific sense, image processing is any type of signal processing that is the input of an image, such as a photo or scene from a movie. The image processor's output can be an image or a set of special symbols or image-related variables.

Most image processing techniques consider the two-dimensional matrix as a signal processor and perform operations on the matrix. To date, multicenter image blending technology has proven to be a valuable method in surveillance and microscopic imaging [3]. Image fusion methods can be divided into single-scale and multi-scale / multi-resolution methods [4]. Pyramid image analysis is the first method introduced in this field and includes reduction pyramid filter, gradient pyramid, Laplacian pyramid, ratio pyramid morphological pyramid, and contrast pyramid [5-10].

Discrete wavelet transform is much more advanced than pyramidal analysis. For example, it can process information required by the human visual system (HVS) [11]. Also, images combined with DWT can achieve better quality [12]. The wavelet has several examples, which are continuous wavelet transform (CWT) and fast wavelet transform (FWT) [13, 14].

Image enhancement aims to improve the interpretation or perception of the information in the image for human viewers or provide better input for automated processing systems. One of the most important quality factors in images is resolution [4]. In image processing, interpolation is used as a known method to increase resolution, referred to as using available data to estimate values in unknown places. Image resolution enhancement methods are based on various interpolations, three of which are the most popular interpolation methods called nearest-neighbor

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interpolation, two-line interpolation, and two-cube interpolation.

Today, wavelet transform is used in many image processing applications, including feature extraction, image noise reduction, compression, face recognition, contrast enhancement, and resolution [15, 16]. It becomes. Decomposition of an image into different frequency ranges allows the separation of frequency components introduced by major shape changes or sub-factors within certain subbands. Considered wavelet-based hybrid models after examining items such as Xu and et al. [3] combined a multi-modal medical image using a matching pulse using an optimized QPSO algorithm, and Daniel Ebenser and et al. [4] worked on image composition using Gray Wolf optimization.

Therefore, to increase the quality of the enhanced images, preserving the edges is a vital issue. Therefore, image resolution enhancement using wavelet transform is a relatively new topic that many methods have recently been proposed in this field. Discretizing a continuous wavelet transform allows you to calculate it with a computer, but this is not a correct discrete conversion. The fact of the matter is that the wavelet series is, in fact, a sampled version of the CWT, and the information they provide, especially when it comes to signal reconstruction, is highly repetitive. This iteration, on the other hand, requires significant computational time and resources.

Combined models such as Xiao and et al. [8] worked on a multi-axis focused image based on edges and focused area extraction and achieved good results. El-Hosny and et al. [9] worked on an efficient DT-CWT medical image, and Ma and et al. [10] worked on an image composition method based on content recognition and achieved good results.

Hybrid models such as Nobariyan et al. [21] and Yin and et al. [18] have been able to get the right answer, but still, wavelet-based methods are better, such Meher and et al. [6] with studied area-based. Zhao and et al. [7] Worked on a local binary pattern based on a centralized metric based on multiple images. Gharbia and et al. [13] Worked on a multi-spectral method and panchromatic image fusion approach using fixed wavelet transform.

Discrete Wavelet Transform (DWT) provides sufficient information about both the parsing and the original signal's composition, with a significant percentage reduction in computation time. This article aims to medical images fusion (MRI and PET) to obtain a quality composite image for study and discover various diseases, especially cancer.

Section 2 describes the methods used to perform fusion, such as wavelet transform. In section 3, the proposed method is presented, and in section 4, the proposed method is evaluated with the help of a medical image database. Finally, in Section 5, a general conclusion of the article is given.

2. Research Methods

2.1 Discrete wavelet transform (DWT)

Wavelet transform obtains signals with different frequencies and provides appropriate information with the help of signal analysis. DWT uses two sets of functions, scale, and wavelet, related to low-pass filters, which are transient [13].

Signal analysis is performed with the help of different frequency bands over time. The main signal in the wavelet is x [n], which is first calculated through a high-pass filter g [n], and a low-pass filter, h [n]. After the filtering operation can delete half the sample according to Nyquist law. The signal at this stage has a maximum frequency of f / 2 instead of f [15]. Can subscribe to the signal with two factors.

The desired formula for wavelet analysis is as follows:

$$y_{high}[k] = \sum_{n} x[n].g[2k-n] \tag{1}$$

$$y_{low}[k] = \sum_{n} x[n].h[2k-n] \tag{2}$$

In it, y_{high} [k] and y_{low} [k] are the output of the high-pass and low-pass filters, respectively, after subsampling [13].

This parsing halves the time resolution because only half of the samples specify the entire signal. Although this operation doubles the frequency resolution because it covers only half of the previous frequency band [6], it effectively halves the frequency's ambiguity. The introduced process is a sub-band coding that can repeat for further analysis. At each model level, filtering and sampling get half the number of samples and half the frequency band. According to Figure 1, x [n] is the main decomposition signal, and h [n] and g [n] are high-pass and low-pass filters, respectively [17]. The signal bandwidth at each level is denoted by f in the figure.

The main frequencies in the signal appear as large oscillations in the area of the wavelet signal that contains certain frequencies. The difference between wavelet transform and Fourier transform is that time information is not lost in wavelet transform.

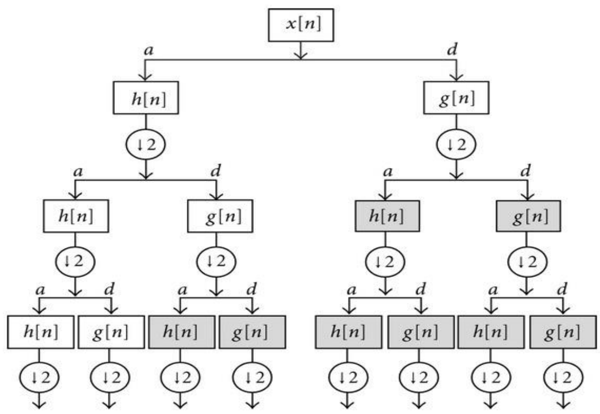

Figure 1. Wavelet with high-pass and low-pass filters [1]

The main signal information is more accurate at high frequencies than at low frequencies. For this reason, more samples are selected at this frequency. Localization will not be very accurate if low frequencies are considered. As a result, few samples are used to express the signal at these frequencies.

One of the platforms that makes the most of this wavelet conversion feature is image processing. You can calculate the DWT of each row for a given image and discard the coefficients below a certain threshold. Then, to recreate the original image's rows, he added the rows to the size of the deleted coefficients of zero and performed the inverse DWT.

It is also possible to parse the image into different frequency bands and use only certain bands to reconstruct the image [15].

2.2 Medical Images

MRI and PET are two diagnostic methods that include non-invasive techniques. "MRI" stands for Magnetic Resonance Imaging. This is a non-invasive method that uses a magnetic field to produce complete and extensive internal organs images [19-22]. MRI is used to monitor physical conditions such as cancer, tumors, and heart problems. This method uses a magnetic field and radio waves. Radio waves are generated to strike tissues that create a contrasting image when the limb is examined. The person being examined is placed under a powerful, ultra-cool magnifying glass, which captures images of the injured part of the body. These are designed to distinguish exactly between healthy and diseased tissues. MRI is used to produce accurate images of most parts of the body.

To diagnose problems such as Abnormal blood flow due to arterial blockage or any other type of injury, Bone or cartilage is also used to find abnormalities in skin tissue. The average MRI scan takes about 20 minutes to 50 minutes, depending on the organ's complexity [6].

"PET" stands for positron emission tomography technique. This technique has been used continuously since the late '50s. PET scanning is also a non-invasive procedure that uses tracer fluid introduced into the body, inhaled, or ingested by the patient.

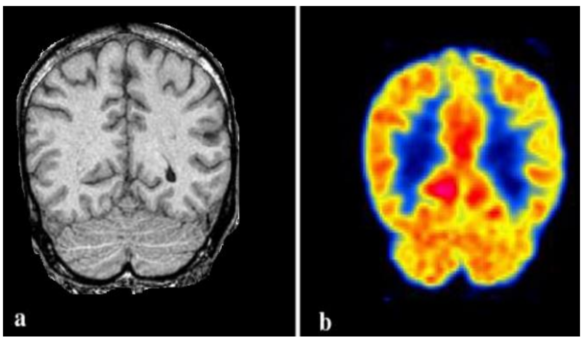

Figure 2. a) MRI image b) PET image [23]

This tracer fluid flows through the plasma throughout the body. A camera is installed that detects particles charged from the tracker fluid. Tracer fluid is a radioactive substance [6]. PET scanning uses nuclear drugs. It also determines the proper functioning of vital organs in the body. In this way, the body's sugar metabolism and oxygen consumption may also be judged. This scan is mainly used to diagnose nervous system disorders such as Alzheimer's and Parkinson's disease. It is also used to diagnose severe cancers and their spread in the body. The PET scan takes about half an hour.

3. Proposed Method

Advances in data collection and storage capabilities have led to large volumes of information in many sciences in recent decades. Researchers in various fields such as engineering, astronomy, biology, and economics face more and more observations every day. Compared to older and smaller data platforms, today's data platforms have created new data analysis challenges. Traditional statistical methods have lost their effectiveness today for two reasons. The first reason is the increase in the number of observations. The second and more important reason is the increase in the number of variables related to observation. The number of variables that must be measured for each observation is called the data dimension. Variable expressions are used more in statistics, while in computer science and machine learning, feature or adjective expressions are used more. Data platforms that are large, despite the opportunities they create, pose many computational challenges. One of the problems with large data sets is that most of the time, all the data features are not critical to finding the knowledge that lies in the data. For this reason, in many areas, reducing the size of the data remains a significant issue.

Data reduction methods are divided into several categories, the best of which are feature-based methods. The feature extraction draws the multidimensional space into a smaller space. In fact, by combining the values of the available properties, they create a smaller number of properties so that these properties have all (or more) of the information contained in the original properties. These methods are divided into two categories: linear and non-linear [24].

Among the linear methods, we can mention DFT and DWT, among which DWT has been considered. Feature selection methods try to reduce the data's size by selecting a subset of the primary attributes. Sometimes data analytics, such as classification, works better on reduced space than on main space. The DWT conversion was first created by a man named Alfred Haar.

Like the Fourier transform, this conversion is widely used and has been considered in many fields of science and engineering. Haar Wavelet conversion is more popular than other DWT versions due to its ease of implementation and high execution speed. This conversion is such that a sequence will be n^2 long inputs.

These numbers are added together in pairs, and these sums are sent to the next step. The difference of each pair is also calculated and stored. This step is repeated, except that the sum of the previous step's pairs is added at the input. This process is repeated recursively to finally obtain a number that is the sum of all numbers. This number is returned along with the $(n-1)^2$ pair difference calculated at different stages of the algorithm as the output of this conversion. DCT and DWT techniques are both algorithms that operate on a frequency range. These techniques divide the image into fixed-size blocks to decide which should select the source image to form the final image.

This paper's technique combines these two algorithms and their improvements in using the criteria that select the best results. The technique described uses the magnitude of the difference as a criterion for selecting the combination of several blurred images in a good quality image. The difference is based on converting the image from the spatial amplitude to the frequency amplitude through DCT calculations. The blur input images are first divided into 8-pixel blocks in which the DCT coefficients are calculated according to the following Formula:

$$d_{k.l} = \frac{c(k)c(l)}{4} \sum_{i=0}^{7}\sum_{j=0}^{7} x_{i.j}(k.l) \tag{3}$$

$$x_{i.j}(k.l) = x_{i.j} cos\,(\frac{(2i+1)k\pi}{16}) cos(\frac{(2j+1)l\pi}{16}) \tag{4}$$

$$c(k) = \begin{Bmatrix} \frac{1}{\sqrt{2}} & k=0 \\ 1 & otherwise \end{Bmatrix} \tag{5}$$

The result is an 8 * 8 matrix of DCT coefficients. Dn = {Dn, k, l} Different block sizes (other than 8 * 8) can also be used to improve results.

The coefficients of each input image are used in the comparison, and the highest values are selected to construct the final image block.

Table 1. Proposed algorithm: DWT and DCT based image algorithm

1) Read the image
2) Apply the DCT function and obtain the parsing table
3) Apply the rules of composition
4) Inverse of DCT function
5) Apply DWT conversion to any image and composite image
6) Calculate the wavelet matrix based on the feature table obtained from the DWT conversion
7) Apply the rules of composition
8) Reverse DWT function to convert to image

The DC coefficient is an exception (0, 0) obtained by simple arithmetic mean between all DC coefficients from the input images. Finally, the image is created with inverse IDCT coefficients. After selecting a block, checking adjacent blocks (in a fixed size window) ensures better image quality of the merged image.

The second step of the proposed system is a wavelet-based system that, using the DCT method described, selects the best feature to combine the two images and then combines the two features of each image with the combination rules' help. And with the help of the wavelet conversion system, the combined image is obtained. The following diagram presents the proposed system, which includes wavelet transform and the use of DCT.

The algorithm consists of 8 steps, and in Table 1, these steps are listed.

In the first step, the images are read, and each image will be stored in the system as a table. The DCT function is applied to the image, and the property table is obtained. The table will feature the DCT coefficients resulting from the function. The combination of high band matrices is done with the help of the maximum function. With DWT conversion, the combined image and input images will be obtained as new feature tables.

In the end, with the help of the average function, the combination will be done, and the inverse wavelet will be obtained.

To provide facts and criteria in the field of accuracy for comparing different spatial evaluation methods and comparing the results of methods, we must have a precise definition of spatial quality. Based on this definition, both reality and different spatial evaluation methods can be analyzed. In general, spatial quality is detecting phenomena and their position with different sizes on satellite images. In images resulting from the merging of the displacement and change of position of different phenomena, we do not have the quality alone assuming accurate geometric correction. The boundaries of different phenomena (edges and borders) are determined and examined. These boundaries have changed in different images, and at the same limits, we can see blurring that is proportional to the spatial quality.

Thus, by measuring different dimensions, the spatial quality of different methods can be accurately determined. With this method, it is possible to study the change in the range of phenomena in different integration methods. It is observed that the differences in the dimensions of different phenomena in the resulting images in comparison with each other and comparison with the original image considering the resolution of the images are a maximum of two pixels. If we pay attention to the measurement method, One or two pixels are usually predictable due to misdiagnosis of the phenomena, so these small differences cannot be emphasized alone.

The main idea in data integration is to generate data from data that has good spectral resolution with the help of data with better spatial power, which has the benefits of both data. Still, this does not happen 100% in practice, and by improving the spatial resolution of multi-spectral data, a percentage of spectral information is lost. Details: In all merging methods, the resulting image is lower than the original images, both in terms of spatial quality and spectral.

To check the validity of the information obtained from the merger in two spatial and spectral dimensions and compare and evaluate different integration methods after the merger, using different quality evaluation methods, such as SNR, PSNR can be checked for quality. Results of payment integration, but it is necessary to mention here that not all of these methods have the accuracy and competence of evaluation. Each of these methods performs an evaluation based on a specific feature and criteria.

4. Tests and Results

In this paper, an image composition framework based on the DWT and DCT hybrid model is presented. The following are some assumptions about how the proposed method is calculated and how. The computational coefficients defined for the wavelet are adjusted based on the wavelet wave. Comparison methods include DCT, DWT, and other methods.

4.1 Evaluation Methods

In general, the purpose of an evaluation is to check the validity of the information obtained from the merger in both spatial and spectral dimensions, as well as to compare and evaluate different integration methods compared to the main multi-spectral and high-resolution images because during the integration process We will have different ratios of spatial properties of high-resolution image and spectral properties of multi-spectral image, i.e., in different stages of implementation of the algorithms used, these properties will change. Therefore, in this study, we study spatial evaluation methods and select the appropriate method or methods in this field. Evaluation of the extent of these changes in image quality is done by two general methods of human comparison and computationally.

In mental methods, a comparison is based on the human visual system. Quantitative evaluation methods use a predefined criterion for comparison, divided into two main categories based on the reference image and independent of it based on the type of criterion. According to Wald, reference-based criteria such as Mapper can be introduced from the non-reference criteria that have recently received much attention, the PSNR (Peak Signal to Noise Ratio) index. PSNR is the most common way to measure image quality, where MAX is the maximum amount of pixels in the image.

$$\text{PSNR}= 10 \log (\text{Max}^2/\text{MSE}) \qquad (6)$$

Here MSE (Mean Squared Error) is the average squared error in finding the number of pixels in an image. The higher the PSNR, the better the image reconstruction. Another indicator is an absolute error. This criterion calculates the distance between the main image and the combined image. The mean of absolute error has been used as a measure of proportionality to determine the correctness. The cost function will be calculated using the MAE error in Equation (7) as follows.

$$d(a,b)=\frac{1}{XY}\sum_{i}^{X}\sum_{j}^{Y}|a(i,j)-b(i,j)| \qquad (7)$$

In Equation (7), a is the evaluation image, b is the target image of the same size, and (i, j) are the pixel coordinates.

The third indicator used to evaluate the combined image is the signal-to-noise ratio (SNR). The signal-to-noise ratio measures the amount of useful signal versus disturbing signal (or noise) in electrical systems. This number is the ratio of signal power to noise power and is expressed in decibels. The higher the index, the better the situation and the more useful the signal strength.

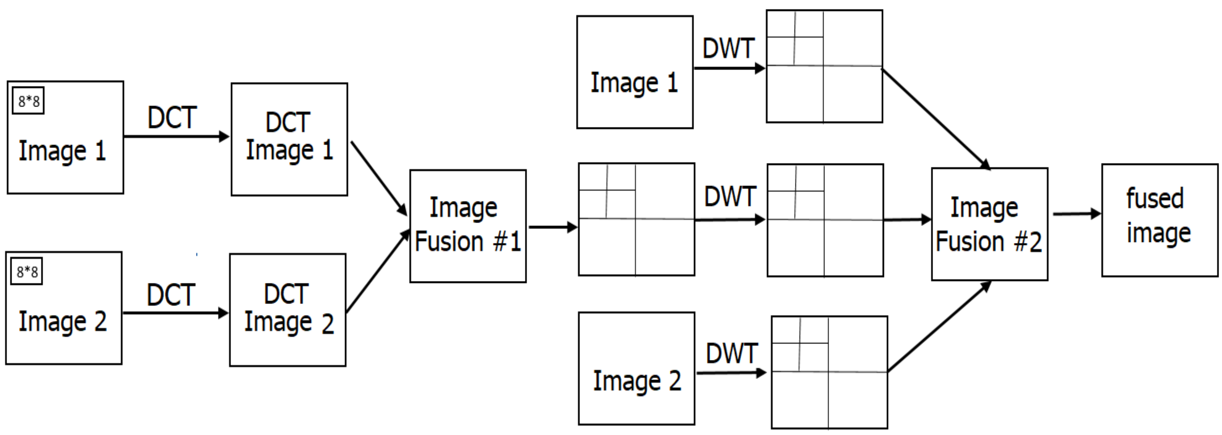

Figure 3. Proposed method image Fusion with DCT and DWT

Equation (8) shows how to calculate the SNR.

$$SNR = 10\log\left(\frac{x^2}{y^2}\right) \quad (8)$$

According to this criterion, x is the average of the pixels, and y is the standard deviation.

All color images used in this test are 256 × 256 with RGB color input type and JPEG format. The simulation was performed on MATLAB R2018b on a personal computer with Intel Core i7, and the calculated results in terms of visual quality and the use of some criteria infusion. The desired values of our analysis scale are mentioned in the conclusion section, and also the results of the proposed fusion framework are compared with SWT methods.

4.2 Data Set

The test data included 150 images of two color domains, PET and black and white high-resolution MRI. Images have 256 x 256 pixels. All images are from the Harvard University website [25]. Brain images are classified into three groups (axial set images, normal coronary images, and Alzheimer's disease). Combining images to compare the algorithms introduced in this article Different images are introduced. For each group, we considered 50 images and the average of the results for comparison.

4.3 Review of Combination Methods

The input image has several problems because the thickness or density of the area to be measured varies.

Therefore, it is important to have a way that cannot be sensitive to this issue. To better understand the composition of the images, the combination is first done with the different methods mentioned (Figure 4).

Figure 5 is a fusion with the help of the proposed method. From the result, we can see that the proposed fusion method can preserve the high spatial resolution properties of the MRI image. Also, the combined image does not distort the spectral properties of the multi-spectral image. Tables 2, 3, and 4 present the composition results based on the image quality criteria. Also, due to the quantitative comparison of different blending techniques, most of the criteria can be obtained with the proposed method, shown in Tables 2, 3, and 4.

To examine each method according to the algorithms, it can be introduced as a table of their performance. Table 2 presents the results for determining the introduced algorithm's quality based on four main methods, and the selected image is MRI and PET image of the human brain in the first dataset.

Table 3 presents the results for the introduced algorithms' quality detection based on four main methods: the selected image, MRI image, and PET image related to the second dataset.

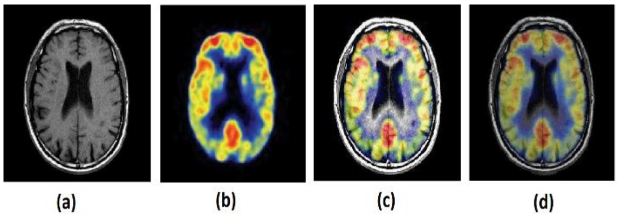

Figure 4. a and b MRI and PET images. d) Fusion of MRI and PET images by DCT method (h) Fusion of MRI and PET images by DWT method [26]

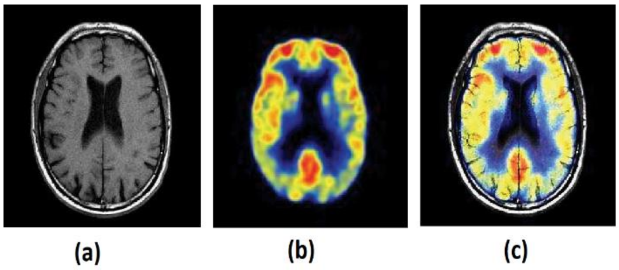

Figure 5. Combining MRI and PET images with the proposed method

Table 2. Results of the above algorithms for MRI and PET imaging of the human brain in the first dataset

Methods	PSNR(%)	MAE(%)	SNR(%)	MSE(%)
PCA	38.21	15.30	44.6	15.650
DWT	39.66	15.01	48.1	15.180
HIS[23]	39.72	14.86	46.02	14.76
SWT[27]	38.19	15.31	47.99	14.55
SWT-DWT[27]	39.34	14.69	46.63	14.23
YCbCr-DWT[22]	40.08	14.11	48.51	13.94
Proposed method	**42.1**	**13.99**	**48.6**	**13.002**

Table 3. Results of the above algorithms for MRI and PET image related to the second data set

Methods	PSNR(%)	MAE(%)	SNR(%)	MSE(%)
PCA	37.12	15.56	44.71	15.13
DWT	39.65	15.97	48.21	15.18
HIS[23]	39.78	14.63	46.03	14.77
SWT[26]	38.23	15.22	47.30	14.52
SWT-DWT[26]	39.44	14.66	46.60	14.27
YCbCr-DWT[22]	40.06	14.13	48.12	13.88
Proposed method	**42.01**	**13.03**	**48.61**	**13.06**

Table 4. Results of the above algorithms for MRI and PET image related to the third dataset

Methods	PSNR(%)	MAE(%)	SNR(%)	MSE(%)
PCA	38.54	15.56	44.55	15.62
DWT	39.12	15.44	48.09	15.17
HIS[23]	39.27	14.37	46.34	14.70
SWT[26]	38.65	15.12	47.98	14.51
SWT-DWT[26]	39.78	14.78	46.60	14.22
YCbCr-DWT[22]	40.90	14.23	48.56	13.90
Proposed method	**42.21**	**13.87**	**48.59**	**13.009**

Table 4 presents the results for quality detection of the introduced algorithms based on four main methods. The selected image, MRI image, and PET image are related to the third dataset.

According to the obtained results, it is clear that the obtained method has obtained a better answer up to about 5% compared to the other introduced algorithms.

5. Conclusion

Multiple images (spatial, spectral, temporal, and radiometric resolution) are ideal for many studies. Therefore, we try to optimize these factors as much as possible in the design of sensors. Still, due to the wide range of applications and technical problems in the design and manufacture of sensors, each sensor is suitable for a specific application and has limitations in other applications.

This is why there are so much variety and diversity in remote sensing imaging systems.

On the other hand, due to the need for data with specifications mentioned in specific applications and the need to use and use existing data from each region, most remote sensing researchers consider data integration or data fusion methods.

Image processing specialists are located. In general, data fusion is easier and more economical than designing and building an advanced sensor that has the power to separate spatially and spectrally. Hence, the use of both spatial and spectral information is undoubted without using data integration methods. They are not possible.

According to the data presented in Section 5, the proposed method was able to provide a somewhat better fusion than the other methods introduced. Also, the point that is evident in this method is that there is no need to manipulate the image in the early stages, which, unlike other methods, will not lead to image preprocessing challenges.

Declaration

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The authors also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

Author Contributions

E. Amiri and M. Rahmanian have defined the main subject. The model has been introduced and implemented by E. Amiri. S. Amiri was in charge of testing and analyzing the data. M. Rahmanian and H. Yazdani wrote the article, and E. Amiri supervised the article's writing.

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