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Medical images fusion based on equilibrium optimization and discrete wavelet transform

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Abstract

Integrating multimodal medical imaging has many advantages for diagnosis and clinical analysis because it creates the conditions for physicians to make more accurate diagnoses. To the best of our knowledge, there are still some disadvantages to current image fusion methods. First, image fusion often has low contrast due to the law of weight average to combine low-frequency components. The second problem is the loss of accurate information in the merged image. This paper presents a waveletbased method and equilibrium optimization for MRI and PET medical image fusion to obtain a highquality image fusion. In the proposed method, the equilibrium optimization algorithm finds the appropriate common points in MRI and PET images and performs the combination with the help of wavelet transform. This allows the welded image to retain the details transferred from the MRI images significantly. Experimental results show that the proposed approach is effective in significantly increasing the quality of the integrated image and preserves the insignificant information transmitted from the input images.

Keywords: Medical Image, Image Fusion, Equilibrium Optimization, Discrete Wavelet Transform.

1. Introduction

The branches of medical sciences [1] are disciplines such as medical engineering, health, physics, chemistry, etc., in which medical image processing is reflected in each branch. Medical imaging began with the discovery of X-rays, and in recent years many efforts have been made to improve the images. At present, due to the great advances in the field of medical imaging, there are still

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limitations in this area, which are more evident in the imaging of the he art and brain because these two parts are vital parts of each The person is in life and is directly related to human life. Another important issue in this field is the processing and results of medical imaging [2], which will affect the doctor's diagnosis, image quality, treatment and recovery time, correct knowledge of the disease, etc. Image processing can occur on a single-mode, multi-mode scale, and each mode will have its results.

Different medical images play an essential role in the clinical diagnosis of modern medicine and help diagnose diseases. To obtain enough information for an accurate diagnosis, physicians usually have to combine several different types of medical images from the same position to diagnose the patient's condition, which often causes great inconvenience. In the medical sciences, computed tomography (CT) scans [3] and magnetic resonance imaging (MRI) [4] are two widely used imaging techniques. However, they do not provide precise details of the structure of the brain. While CT scans are generally performed to image hard tissues and bone structure, MR results are good for delicate imaging tissues in the brain that have a valuable role to play in identifying the disease affecting the skull. These images are interdependent and interdependent, and no single image alone is sufficient for unique data content. Effective use of medical imaging is in hybrid imaging, which includes infinitesimal imaging, PC vision, remote diagnosis, and clinical imaging. Suppose several types of medical images are analyzed only by spatial concepts and physician conjectures. In that case, the accuracy of the analysis will be subjectively affected, and even parts of the image information may be overlooked. Image fusion techniques [5] offer a more effective way to solve these problems.

Medical image processing is one of the most important topics in medical sciences, and its impact on executive and practical topics such as surgery, treatment, and medical research cannot be ignored. Medical image processing is now more commonly referred to as digital image processing. It is a branch of computer science that deals with digital signals representing images taken with a digital camera or scanned by a scanner. Image processing has two main branches: improving the image and vision of the machine [6]. Multimodal medical image fusion is a combination of multiple images from single or multiple imaging techniques. Medical image fusion aims to improve imaging quality by maintaining specific features to increase the clinical application of images to diagnose and evaluate medical problems. Medical image fusion techniques cover a wide range of areas, including image processing, computer vision, pattern recognition, machine learning, and artificial intelligence, which are widely used in clinics for physicians in understanding the lesion and combining these methods with methods. The other is for better diagnosis.

Multi-center image composition is a method by which several images on a screen, each focusing on different objects, are enhanced so that all objects appear to be focused in the final image. To date, multicenter image blending technology [7] has proven to be a valuable method in surveillance (e.g., in CCTV) and microscopic imaging. With the proliferation of medical imaging devices, medical images obtained from various methods contain complementary and redundant information. Medical image fusion techniques can combine multimodal medical images for a more reliable and accurate medical diagnosis. Image composition methods can be divided into two methods: single-scale methods and multiscale / multi-resolution methods. Pyramid image analysis [8] is the first method introduced in this field and includes reduction pyramid filter, gradient pyramid, Laplaceon pyramid, ratio pyramid, morphological pyramid, and contrast pyramid.

It should be noted that several scales and several resolutions have an advantage in image fusion cognitive research in which Wavelet Transform has a special and important role. Discrete Wavelet Transform (DWT) directional information [9] exists at several levels of analysis and exhibits distinctive features at various resolutions. The waves are estimated due to the shift change; the fused image does not form an edge. The change type problem is solved by fixed waveform [10], respectively. The images below are fuzzy and fuzzy under the idea of a fused image. Therefore, fuzzy logic is used to create uncertainty in the images infusion. Multiple levels of image fusion analysis using sequence wavelet transform(SWT) ensure better fusion results. Note that fusion commands based on SWT algorithms are specific and explicit. Therefore, accurate spectral and spatial information is not distorted and is preserved.

Discrete wavelet transform is much more advanced than pyramidal analysis [21]. For example, it can record directional information essential for the human visual system (HVS) [11], , and images combined with DWT can obtain a higher signal ratio. Other examples of wavelet transform are wavelet transform, violet transform, curvelet transform, and contour volt conversion [12].

Today, wavelet transform is used in many image processing applications, including feature extraction, image noise reduction, compression, face recognition, contrast enhancement, and resolution. Decomposition of an image into different frequency ranges allows the separation of frequency components introduced by changes in the main shape or sub-factors within certain sub bands [22]. Because resolution enhancement by direct use of interpolation due to high-frequency components such as edges creates a soft image. 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 has recently been proposed in many ways. Discontinuing a continuous wavelet transform allows calculating 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. Discrete Wavelet Converter provides sufficient information about both the parsing and the composition of the original signal, with a significant percentage reduction in computation time.

Integrated medical imaging techniques have been widely used in clinical diagnosis. Scalability techniques Based on known techniques in moving image fusion, generalized scaling has a static scale that destroys the quality of fusion. Ebenezer et al. [13] have introduced a medical image fusion method using the gray wolf optimization algorithm. This method was based on scaling. Optimum Spectrum Mask Fusion has been used to combine medical images based on optimization graphics. The proposed method is then tested on various brain images, and the final results show the system's ability. The optimal values for the scale parameters have been selected based on a new hybrid optimization approach called the "Shark Odor Optimization Algorithm."

In the following, in Section sec2, the background of the research is given. Then, the optimized DWT is presented in Section sec3 of the analysis and research methodology. System performance is evaluated in Section sec4, and the structure of the proposed algorithm is reviewed. The result of the article is presented in Section sec5.

2. Research background

A review of recent publications on medical image processing techniques shows that these publications are classified according to a model with nine salient criteria, the main duality of which is exogenous versus intrinsic methods. Classification statistics show specific trends in evolving registration techniques that will be discussed. Medical image fusion is one of the important processes of medical image processing that involves recording and combining several images from single or multiple imaging methods to improve imaging quality and reduce randomness and redundancy to increase the clinical application of medical images to diagnose and evaluate medical problems. Algorithms and devices that perform medical image fusion [14] have increased the accuracy and speed of disease diagnosis. The research articles provide a list of methods presented and summarize the vast scientific challenges in medical image integration. We describe medical image composition research based on

(1) widely used image fusion techniques, (2) imaging techniques [15], and (3) imaging of the organs under study.

In general, it can be said that previous research on the composition of medical images has achieved the benefits of faster computation, dynamic scale selection, ease of use for combining medical images, improving the quality of medical image edges [16], but still, a significant result in speed Enabling each step of image composition, enhancing edge quality, and enhancing the quality of medical images, which is of great importance in the field of health, medicine, and artificial intelligence, is forcing researchers to do more research in this area.

In 2019, Meher, B. et al. [8] studied area-based image composition methods and achieved the following results. Image integration is emerging as an important area of research. This program has attracted many applications such as monitoring, photography, medical diagnosis, etc. Image blending techniques have been developed at three levels: pixel, feature, and decision making. Area-based image fusion is one of the feature-level methods. This special advantage - less noise than noise and prevents reregistration. This paper provides an overview of area-based fusion approaches.

Wavelet transform is one of the important mathematical transformations that is used in various fields of science. The main idea of wavelet transform is to overcome the weaknesses and limitations of the Fourier transform. Unlike Fourier transform, this conversion can also be used for non-static signals and dynamic systems. DWT analyzes the signal at different frequencies with different resolutions by decomposing the signal into general approximation and detailed information. DWT uses two sets of functions, scale functions and wavelet functions related to low-pass filters, and They are transient. Signal decomposition into different frequency bands is done by sequentially filtering the high-pass and low-pass signals over time.

Wavelet transform is as widely used as Fourier transform [17] and has been considered in many fields of science and engineering. Haar Wavelet conversion [18] is more popular than other versions of DWT due to its simplicity 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 pairs is added at the input. This process is repeated in reverse 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 conversion output.

In 2018, Nair, R.R. and T. Singh. [19] worked on combining the medical image of several sensors using pyramid-based DWT and achieved the following results. In general, image fuses are performed on 2D images, but operations with 2D images increase computational complexity over vector data. This study presents a Laplace pyramid algorithm based on a discrete wavelet transform called DWT Resolution Modified (MMDWT) to combine a multi-sensor medical image efficient for n-level analysis and work with all mothers. Wavelets that have less computational complexity.

In 2019, Joshi, K., et al. [17] worked on fusing a multi-center image using the discrete wavelet transform method and achieved the following results. Combining a multi-center image is a fundamental way to integrate important information from an image database with a similar scene. The fused image can be more informative than any previous source image. In this paper, a new scheme based on discrete wavelet evolution is presented. Multi-center images are decomposed at different levels and with relevant fusion criteria such as standard deviation (SD), correlation coefficient (CC), entropy, etc. Used to produce more processes. Finally, multi-center images are all in one center. This experimental experiment has been used to produce good quality scale images. The research work had a significant impact on the qualitative approach.

In 2016, Xu X. et al. [24] worked on medical image fusion using a discrete fraction wavelet transform and achieved the following results. In this paper, a method of combining multistage medical images based on discrete fraction wavelets is presented. Changing the p order in the range (0 1) decomposes the source medical images by the indifferent P order DFRWT. The rare feature of state coefficients changes in the underlying images. According to the Toteh method, to strengthen the correlation between sub-band coefficients, non-scatter properties of themes should be used at low p levels, respectively. The coefficients of all sub-bands are weighted using the regional variance law, and finally, the inverse DFRWT is used to obtain a composite image.

One of the most cost-effective and simplest problem-solving techniques (in terms of computational load and time required to implement the algorithm) in the field of artificial intelligence is evolutionary computational methods. In general, evolutionary computational algorithms are based on applying Darwin's theory of evolution to the implementation of computer programs. One of the important goals of evolutionary computational methods and evolutionary algorithms, in particular, is to improve the quality of poorly generated solutions to a given problem. To improve the quality of poorly produced solutions, evolutionary computational algorithms use evolutionary processes; In other words, evolutionary computational algorithms, in an iterative process, manipulate the poorly generated solutions so that the system can solve the problem with the desired accuracy.

In 2017, Daniel E. et al. [13] worked on an optimal spectrum mask based on a medical image composition using gray wolf optimization and achieved the following results. In this paper, the optimal spectrum mask algorithm is proposed to integrate the medical image using the Gray Wolf Optimization Algorithm (GWO).

In 2016, Xu X. et al. [25] combined a multimodal medical image using a matching pulse using an optimized QPSO algorithm and achieved the following results. This paper proposes a method for integrating multimodal medical images using Neural networks with matching pulses, optimized by the Behavioral Quantum Particle Optimization Algorithm. In this combination model, two source images, A and B, were processed by the QPSO-PCNN model, respectively. Through the QPSO algorithm, the PCNN model can find optimal parameters for source images, A and B to improve QPSO performance and quality, three evaluation criteria, image entropy (EN), mean slope (AG), and spatial frequency (SF). They were selected as the hybrid function. Then, the output of the fusion model is obtained by the coefficient of judgment according to the firing drawings of the two source images, which may be the pixel value of image A or image B, the value of their renewability. Based on the output of the composition model, a fused image was obtained. Finally, we used five pairs of multimodal medical images as experimental data to test and validate the proposed method. In addition, cross-information (MI), structural similarity (SSIM), image entropy (EN), etc., have been used to judge the performance of various methods. Experimental results show that the predicted method shows better performance.

In 2019, Niu, P., S. Niu, and L. Chang. [27] worked on a defect in the gray wolf optimization algorithm and its verification method and achieved the following results. The Gray Wolf optimization algorithm is a new meta-exploratory optimization technology. Its essence is to mimic the behavior of gray wolves in the wild for participatory hunting. GWO differs from others in terms of model structure. This is a large-scale search method that focuses on three optimal samples and is also the goal of many researchers. In this study, this article found that GWO is defective. This works well for the optimization problem where the optimal solution is 0; however, its advantage is not as clear as before and even worse for other problems. It becomes clear that when GWO solves the same optimization performance, the optimal solution is farther away, and its performance is worse. This defect appears in other optimization algorithms as well. By studying this defect, the analysis is done, and the reason is determined. Finally, although there is no way to normalize GWO, this paper offers a validation method to avoid this problem and help develop an optimization algorithm.

Ozsoydan, F.B. [26] in 2019 worked on the effect of dominant wolves in the gray wolf optimization algorithm and achieved the following results. Bio computing is one of the soft computing techniques emerging in the last decade. Although they do not guarantee optimization, the main reasons why such algorithms become popular are, in fact, the simplicity of implementation and openness to various improvements. Inspired by the hierarchical order and hunting behaviors of gray wolves in the wild, the Gray Wolf algorithm is one of the new generation-inspired biological metaphors. GWO was first introduced to solve global optimization and mechanical design problems. In the next step, it is used for different types of problems. As reported in several publications, GWO is a good algorithm; however, the effects of specific GWO mechanisms on solution quality have not been sufficiently discussed in the relevant literature. Accordingly, the present study examines the effects of dominant wolves, which have important effects on GWO searchability, and introduces new dominant extensions based on wolves' changes.

As we know, mass is the imperishable property of matter and always remains constant, so in any process, it can be said that the mass of the reactants is equal to the mass of the substances formed during the reaction. The balance of crime is, in fact, the law of survival of the fittest, which states that crime neither disappears nor arises but changes from one state to another. Mass balance is defined in a system. Mass balance is an obvious issue and one of the basic rules. Mass balance equations are always a basic prerequisite for calculations in solving engineering problems. These rules are always constant, and their equations are in equilibrium. The inputs and outputs of these equations are always equal, so we can say that these equations produce an output.

In 2020, Faramarzi, A. et al. [30] worked on a new optimization algorithm on equilibrium optimization and achieved the following results. This paper uses a new optimization algorithm called Optimibrium Optimizer (EO), inspired by mass balance volume control models, to estimate dynamic and equilibrium states. In EO, each particle (solution) acts as a search agent with its concentration (position). Search agents randomly update their concentration according to the best available solutions, i.e., equilibrium candidates, to finally reach equilibrium (optimal result). The well-defined term "production rate" has been shown to enhance the EO's ability to explore, exploit and avoid the local minimum. The proposed algorithm is calculated with 58 non-mod functions, multiple modes and combinations, and three engineering application problems. EO results are compared with three existing optimization methods, including: (i) The most well-known meta-innovation, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO); (ii) Recently developed algorithms, including Gray Wolf Optimizer (GWO), Gravity Search Algorithm (GSA) and Salp Congestion Algorithm (SSA); And (iii) high-performance optimizers, including CMA-ES, SHADE, and LSHADE-SPACMA.

In 2020, Wunnava A. et al. [29] worked on a multi-level threshold method based on interdependence using a compatible equilibrium optimizer and achieved the following results. The multi-level threshold is one of the most important measures in computer vision, a subset of artificial intelligence (AI) used to understand and interpret data in the real world. Existing entropic methods based on a histogram of an image for a multi-level threshold deal with maximizing entropic information except for the shredding boundary, which reduces accuracy. These problems lead to poor threshold accuracy and lower speeds. We propose a new interdependence-based method that uses the fragmentation boundary, a minimization problem, to solve this problem. A first-hand target function is examined, which takes care of the crushing boundary. Traditional multi-level threshold techniques are computationally expensive due to the comprehensive search process, an alternative to using evolution-based algorithms based on nature-inspired algorithms. In this paper, a new optimizer called Adaptive Equilibrium Optimizer (AEO) is also proposed for the multi-level threshold, improving the fundamental equilibrium optimizer (EO) by implementing adaptive scattering decisions for non-performing search agents.

In order to find the optimal results, combining the image with the help of a wavelet is one of the methods that researchers study. In addition to methods such as wavelet transform, there are many methods in image composition, some of which can be described as follows.

In 2018, Tian, J. and other [3] worked on a multi-focal focused image based on edges and focused region extraction and achieved the following results. The goal of multi-focused image focus is to connect multiple near-focused images to a clearer image. The first type of edges, prominent concentrated edges, exist only in concentrated areas. They are passed through the upper purification images through the threshold method, and then the source images are used to identify the concentrated areas based on the frame structure. The second type of edges synthesized by Canny edges is used to modify the boundaries of concentrated areas. Finally, the extracted concentrated areas are combined into a clear image. Experiments show that the proposed algorithm can extract focused areas with appropriate boundaries. Thus, fused images can avoid the use of distortion and be focused on objects. The proposed method improves some of the advanced algorithms in terms of visual quality and quantitative indicators.

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 challenges in data analysis. 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 multi-dimensional data is that most of the time, all the properties of the data are not vital 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. Feature-selection methods [30] try to combine better images by selecting optimal subsets of primary features.

try to combine better images by selecting optimal subsets of primary features. In this section, a new multi-objective method for combining medical images is presented. This method is provided with a combination of discrete wavelet transform methods and a consistent equilibrium optimizer. The proposed method aims to obtain an optimal image of the composition of medical images using coatingbased techniques. The equilibrium optimization algorithm uses the important topic of mass balance to select the optimal scales and cover the Formula. The block diagram of the proposed algorithm is shown in Figure 1, in which, using the equation, the input image criteria are converted to Fourier space and discrete wavelets. The first image and the second image show the input images. Discrete wavelet transforms, Fourier space is the image of the spatial domain. The EO algorithm [29] is used to optimize the Fourier spectrum of input images and the optimal scale of inputs. In the feature combination by wavelet and EO, the basic features of the specified images and the details of the input image information are expressed (Figure 1). Then the first and second optical images of the results obtained from feature extraction are melted using pixel-based averaging. The resulting molten image is obtained in the February range. Inverted Fourier transform is used to capture a spatial image with a spatial range.

In the first step, the images are read, and each image will be stored in the system as a table. The DWT function is applied to the image, and the property table is obtained. The DWT technique is an

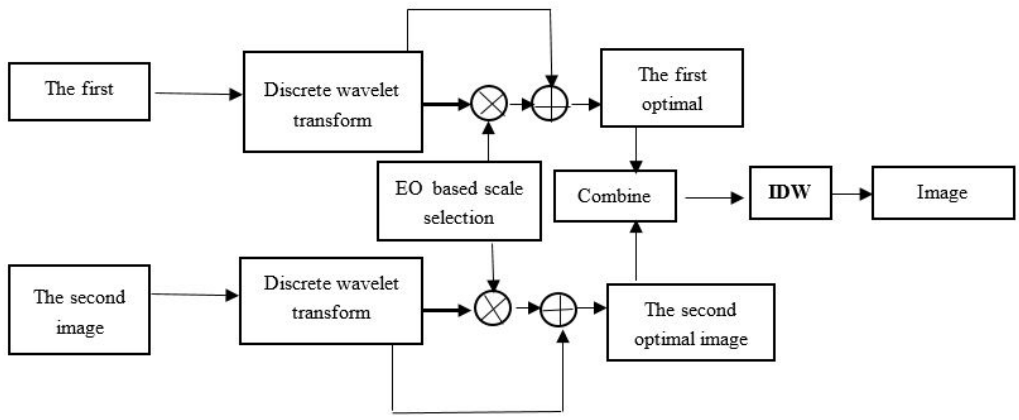

Figure 1: Image composition algorithm with the help of wavelet combination and equilibrium mass

algorithm that operates on a frequency range. This technique divides the image into fixed-size blocks to decide which source image should be selected to form the final image. The main signal x [28] is first passed through a high-pass filter g [n], half band, and a low-pass filter, h [n]. After the filtering operation, half of the samples can be removed according to the Nyquist rule because the signal at this stage has a maximum frequency of f / 2 instead of f. Hence the signal can be subscribed with a factor of two. This represents a level of decomposition and can be represented as follows formula 3.1 and 3.2.

$$y_{high}[k] = \sum_{k=1}^{n} x[n].g[2k-n] \tag{3.1}$$

$$y_{low}[k] = \sum_{k=1}^{n} x[n].h[2k-n] \tag{3.2}$$

In it, y high [k] and y low [k] are the output of the high-pass and low-pass filters, respectively, after subsampling. This parsing halves the time resolution because only half of the samples specify the entire signal. Although this operation doubles the frequency resolution because the frequency band currently covers only half of the previous frequency band, it effectively halves the ambiguity in the frequency. The above process, also known as sub band encoding, can be repeated for further parsing. At each level, filtering and subsampling result in half the number of samples (and hence half the time resolution) and half the frequency band (and therefore twice the frequency resolution). Figure 2 illustrates this process, in which x [n] is the main signal for decomposition, and h [n] and g [n] are the high and low pass filters, respectively. The signal bandwidth at each level is denoted by f in the figure.

The most prominent frequencies in the main signal appear as large oscillations in an area of the DWT signal that contains specific frequencies. The difference between this conversion and the Fourier transform is that the temporal information of these frequencies is not lost. Time localization has a resolution that depends on the level at which these frequencies appear. If the main information of the signal is at high frequencies, what happens is that the localization of these frequencies is more accurate. Hence, a larger number of samples characterize these frequencies, but if the original information is only at low frequencies, the localization will not be very accurate. A small number

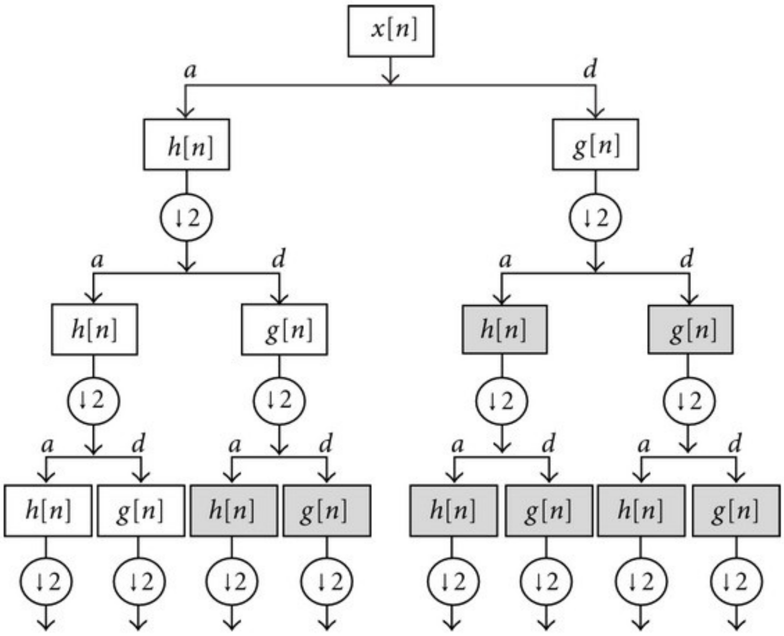

Figure 2: Wavelet with high-pass and low-pass filters [27]

of samples will be used to express the signal at these frequencies. As a result, this process provides good time resolution for high frequencies and good frequency resolution for low frequencies.

One of the platforms that makes the most of this wavelet conversion feature is image processing. As probably know, images, especially high-resolution images, require a lot of storage space. DWT can be used to reduce image size without greatly reducing resolution. Now see how this is done. For a given image, one can calculate the DWT of each row and discard the coefficients that are below a certain threshold. Then, to recreate the rows of the original image, he added zero to the rows equal to the deleted coefficients 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.

According to Algorithm 1, we proposed an optimal spectrum mask combination to overcome the contrast constraints in conventional methods. The optimal scale values are selected using the recently introduced optimization algorithm called equilibrium optimizer.

Table 1: Proposed algorithm: DWT and EO based image algorithm

Line	Algorithm execution procedure
(1)	Read the image
(2)	Apply the EO function and obtain the parsing table
(3)	Apply the rules of composition
(4)	Inverse 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

For a mass balance equation written on a system, it can be said that the amount of mass entering the system is equal to the amount of the first output masses plus the amount of the second output masses if there is no accumulation or storage in the system.

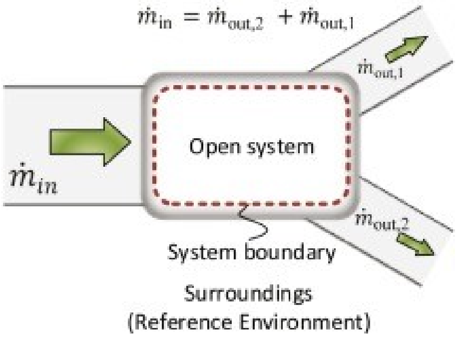

Figure 3: Input and output in the mass balance equation

In the cases that arise in the accumulation system, the stable energy equation and the general equilibrium state of the equation must be maintained on the other side, i.e., the sides of the equation must be equal again.

$$V\frac{dc}{dt} = QC_{eq} - QC + G \tag{3.3}$$

In the above equation, the algebraic sum minus the input minus the output plus the mass generation rate equals how many changes occur per second on the input. In this equation on the first side, V is the unit of volume, and its unit is cubic meters, dc is the differential derivative of concentration changes. Its unit is kilograms per volume, dt is the differential derivative of time changes that dc / dt is the rate of volume change for us, C The mass is in one cubic meter, and since factors, V and C are cubic meters, $V^{*}dc$ is equal to kilograms and the whole unit to the left is equal to kilograms per second.

On the other side and to the right of this equation is C equilibrium and its unit in kilograms per cubic meter, Q flow rate (flow rate passing through a system point per unit time) and its unit in cubic meters per second, then $Q * C$ as input and its unit in kilograms in Counts as seconds. It should be noted that the input of the problem is initially considered in equilibrium. QC is the concentration that leaves the control volume, G is the mass production within the control volume. With the above explanations, it can be said that the above equation is a first-order differential equation, which is, in fact, the general equation of mass equilibrium, in which the change in mass in time is equal to the amount of mass entering the system plus the changes produced. Alternatively, deleted within the control volume minus the value logged out. If there are no changes in the system, i.e., $V^{dc/dt}$ reaches zero, and a stable equilibrium state is achieved. Stable equilibrium means that no change in an equation occurs over time, and the parameters of the equation do not change over time. So, in general, it can be said that when the input and output of the equation are fixed and do not change, a steady state of equilibrium is achieved. To convert the equation to a linear equation, rearrange the equation slightly. To obtain a linear equation, we must subtract the coefficient of the equation and divide the sides of the equation by V, and finally consider $\lambda = Q/V$, and the result will be the following equation:

$$\frac{dc}{\lambda C_{eq} - \lambda C + \frac{G}{V}} = dt \tag{3.4}$$

Note: We consider C to be a function of time and other parameters to solve the concentration in the control volume. When we take integrals from the differential equation, we can delete the differentials and turn them into parameters. The integration of Equation 4 overtime gives the following equation:

$$\int_{C_0}^{C_1} \frac{dc}{\lambda C_{eq} - \lambda C + \frac{G}{V}} = \int_{t_0}^{t} dt \tag{3.5}$$

In the above equation, t_0 is the starting time, and c_0 is the initial concentration, dependent on the integration parameters. Finally, the following equation estimates the concentration in the control volume with the known circulation rate, which is implemented as linear regression.

$$C = C_{eq} + (C_0 - C_{eq})F + \frac{G}{\lambda V}(1 - F) \tag{3.6}$$

Which is the above equation F is calculated as follows.

$$F = \exp\left[-\lambda(t - t_0)\right] \tag{3.7}$$

After obtaining the optimal spectrum mask composition with the help of the EO optimization method, its convolution conversion will be calculated with the matrices obtained from the wavelet transform, which will be performed as follows.

$$x[n] = \sum_{k=-\infty}^{+\infty} x[k]\delta[n-k] \tag{3.8}$$

Convolution calculation causes the loss of some important features of the discrete wavelet. To restore the information about the wavelet, we add its values to the matrix obtained from the wavelet transform. The optimal images obtained from this operation are used in the composition phase. Combining the average of the lower wavelet wave and the maximum of the middle and upper waves of the wavelet can be calculated with formulas 3.9 to 3.12.

$$LL = \frac{(LL1 + LL@)}{2} \tag{3.9}$$

$$LH = \max\left(LH1 \cdot LH2\right) \tag{3.10}$$

$$HL = \max\left(HL1 \cdot HL2\right) \tag{3.11}$$

$$HH = \max\left(HH1 \cdot HH2\right) \tag{3.12}$$

The result of the composition algorithm is a matrix whose values are obtained from the wavelet. To obtain a composite image, we must obtain the result of the matrix obtained from the wavelet in reverse. As a result, the resulting matrix will be an optimal composite image with the characteristics of PET and MRI images simultaneously.

In order to provide facts and criteria in the field of accuracy for comparing different methods of spatial evaluation and comparing the results of methods, we must have a precise definition of spatial quality and, based on this definition, both reality and different methods of spatial evaluation can be analyzed. In general, spatial quality detects phenomena and their position with different sizes on satellite images. In the images resulting from merging the displacement and change of position of different phenomena, assuming accurate geometric correction, we have no quality and quality alone. The boundaries of different phenomena (edges and borders) are determined and examined. These boundaries have changed in different images, and in the same range, we can see blurring 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 different integration methods. It is observed that the dimensional differences of different phenomena in the images resulting from the merger in comparison with each other and comparison with the original image considering the resolution of the images, is a maximum of two pixels, and 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. However, in work, this does not happen 100%, and by improving the spatial resolution of multispectral data, a percentage of spectral information is lost. Details: In all merging methods, the merged image is lower than the original images in both spatial and spectral quality.

In order to check the validity of the information obtained from the merger in two spatial and spectral dimensions and compare and evaluate different methods of integration after the merger, using different quality evaluation methods, such as SNR, RMS can check the quality Results of payment integration. However, it is necessary to mention here that not all of these methods have the accuracy and competence of evaluation because they perform an evaluation based on a specific feature and criteria.

4. Experimental setup

4.1. Data set

MRI and PET are two diagnostic methods that include non-invasive techniques. "MRI" stands for Magnetic Resonance Imaging and a non-invasive method that uses a magnetic field to produce complete and extensive images of internal organs [23]. 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 created to hit tissues that create a contrasting image when the limb under examination is restored. The person being examined is placed under an extremely powerful and extremely cooled magnifying glass, which then 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, such as abnormal blood flow due to arterial blockage or any other type of injury. The average MRI scan takes about 20 minutes to 50 minutes, depending on the complexity of the organ.

"PET" stands for Positron Emission Tomography Technique [20]. 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. This tracer fluid flows through the

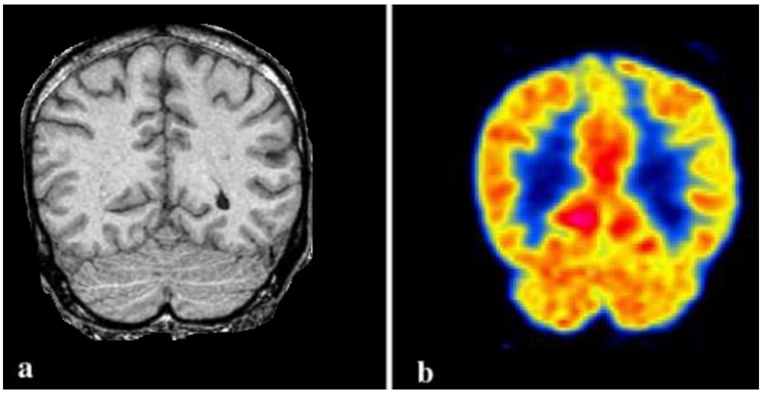

Figure 4: (a) MRI images (b) PET image

plasma throughout the body. A camera is installed that detects particles charged from the tracker fluid. Tracer fluid is a radioactive substance. 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 disorders of the nervous system such as Alzheimer's disease and Parkinson's disease. It is also used to diagnose severe cancers and their prevalence in the body.

Test data includes 150 images of two color domains, PET and black and white high-resolution MRI. Images have 256×256 pixels. All images are from the Harvard University website (http://www.med.harvard.edu/AANLIB/home.html). Brain images are classified into two groups (axial set images and normal coronary images). 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.

4.2. System Implementation

In this paper, an image composition framework based on the DWT and EO hybrid model is presented. In the next section, various assumptions are made about how the proposed method is calculated and how. The computational coefficients defined for the wavelet are set based on the wavelet wave. Comparison methods include PCA, DWT, and MRAIM.

4.3. Evaluation metrics

In general, the purpose of the 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-spectrum and high-resolution images because during the integration process according to the method used. We will have different ratios of spatial properties of high-resolution images and spectral properties of multispectral images. In different stages of implementation of the algorithms used, these properties will change. For this purpose, in this research, we examine the methods of spatial evaluation and select the appropriate method or methods in this field.

Evaluation of the extent of these image quality changes is done by two general methods of human comparison and computationally. In mental methods, the 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 index. PSNR is the most common way to measure image quality, where MAX is the maximum amount of pixels in the image.

$$PSNR = 10\log(Max^2/MSE) \tag{4.1}$$

Here MSE 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 Formula 4.2 as follows.

$$d(a,b) = \frac{1}{XY}\sum_{i}^{X}\sum_{j}^{Y}\Big|a(i,j) - b(i,j)\Big| \tag{4.2}$$

In formula 4.2, a is the image of the evaluation, b is the target image with the same size, and (i, j) pixel coordinates.

The third indicator used to evaluate the combined image is the signal-to-noise ratio (SNR). The signal-tonoise ratio measures the amount of useful signal versus annoying 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. Formula 4.3 shows how to calculate the SNR.

$$SNR = 10\log\left(\frac{x^2}{y^2}\right) \tag{4.3}$$

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 in fusion. 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 and other method.

5. Results and discussion

The input image has several problems because the thickness or density of the required area to be measured varies. Therefore, it is important to have a way that is not sensitive to this issue. In order to better understand the composition of the images, first, the combination with the mentioned different methods has been done (Figure 5).

Figure 6 is a combination with the help of the proposed method. From the result, it can be seen that the proposed combination method can preserve the high spatial resolution properties of the MRI image. In addition, the combined image does not distort the spectral properties of the multispectral image. Tables 2 to 5 present the composition results based on the image quality criteria. In addition, due to the quantitative comparison of different combining techniques, most of the criteria can be obtained with the proposed method, which is shown in Tables 2 to 5.

In this section, MR and PET images from two clinical cases are used for fusion analysis. The first parameter was a 50-year-old man with grade 4 astrocytoma who needed medical attention due

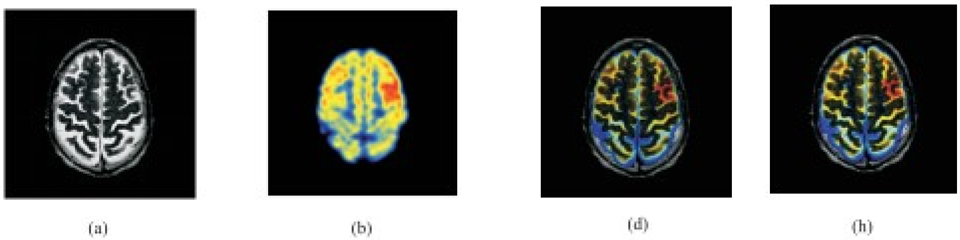

Figure 5: The (a) and (b) MRI and PET images. (d) Combination of MRI and PET images by PCA method (h) Combination of MRI and PET images by DWT method.

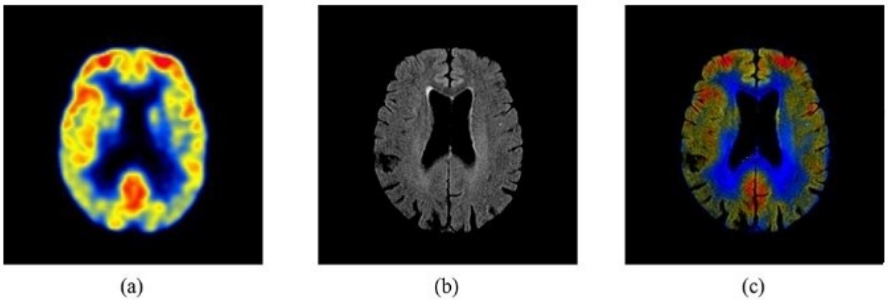

Figure 6: Combining MRI and PET images with the proposed method

to a large seizure. The second parameter was a 73-year-old man with grade 2 astrocytoma who had difficulty progressing in speech and seizures. Both input images are shown in Figure 5. In it, functional PET is plotted on the anatomical MR structure. The quantitative results of the proposed algorithm with different techniques are given in Tables 2 and 3. The target results of our fusion technique are shown in Figure 6.

Table 2: Results of MRI and PET image analysis of the human brain in the first dataset

	Proposed	IHS	FFT	DWT	DCT
MI	3.4029	2.7131	3.3232	2.8098	3.1989
Entropy	5.4120	5.3889	5.2877	5.2898	5.2399
$Q^{AB/F}$	0.0670	0.0318	0.0501	0.04960	0.0539
STD	57.6678	47.1225	45.5990	45.1263	45.1073

Table 3: Results of MRI and PET image analysis of the human brain in the second dataset

	Proposed	IHS	FFT	DWT	DCT
MI	2.9822	2.2123	2.4963	2.1903	2.3093
Entropy	3.7917	3.5414	3.2753	3.1993	3.1102
$Q^{AB/F}$	0.0897	0.0409	0.0694	0.0527	0.0612
STD	64.7084	47.8963	45.1057	42.1190	45.0996

In order to be able to examine each method according to the algorithms, it can be introduced as a table of their performance. Table 4 presents the results for determining the quality of the introduced algorithm based on four main methods. The selected image is the MRI and PET image of the human brain in the axial images dataset.

Table 4: Results of the above two algorithms for MRI and PET imaging of the human brain in the axial images dataset

Methods	MSE	SNR	MAE	PSNR
PCA	15.550	45.7	17.50	37.11
DWT	15.440	49.2	17.21	38.56
HIS [23]	14.56	47.12	16.96	38.62
SWT[24]	14.15	48.09	17.51	37.09
SWT-DWT[24]	14.03	47.73	16.89	38.24
YCbCr-DWT[25]	13.99	49.61	16.31	39.02
Proposed method	13.92	49.71	15.99	41.11

Table 5 presents the results for quality detection of the two introduced algorithms based on the four main methods, the selected image, MRI image, and PET image related to the normal coronary images dataset.

Table 5: Results of the above two algorithms for MRI and PET image related to the normal coronary images dataset

Methods	MSE	SNR	MAE	PSNR
PCA	13.13	48.31	16.22	36.63
DWT	13.08	49.89	15.74	36.86
Proposed method	11.57	50.79	15.24	40.14

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

6. Conclusion and results

Medical imaging is an important issue in medicine regarding its effectiveness and sensitivity in diagnosing various medical topics. In general, compiling a comprehensive picture that includes all the useful features of medical images will help specialists diagnose the disease more easily and accurately. The process of combining different information in images and combining them is called image integration. A new and optimal hybrid method based on the equilibrium optimization algorithm and wavelet decomposition position for multimodal medical image fusion is introduced in this study. This method gathered both the advantages of the wavelet analysis and mass balancing methods in a single configuration. This method can improve the efficiency of the fusion system by combining functional and descriptive features. To develop system performance, a new hybrid optimization algorithm, called Hybrid Shark Odor Optimization, is proposed based on the World Cup optimization algorithm and is used for optimal wavelet system analysis. The optimization part is used in later parts such as wavelet input and output to find the optimal parameters for frequencies and the fusion part to combine low-pass filters and high-pass filters optimally. These simulations were applied in two different groups of clinical images. The experimental results demonstrate system performance compared four different methods of medical image fusion. Since multiple images (in terms of spatial, spectral, temporal, and radiometric resolution) are ideal for many studies, it tries to optimize these factors as much as possible in the design of sensors, but due to the wide range of applications and problems. Technically in designing and manufacturing sensors, each sensor is suitable for a specific application and has limitations in other applications, so there is a great variety and multiplicity 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 image processing experts and comments have considered most data integration or data fusion methods. Researchers have attracted remote sensing. In general, data fusion is easier and more economical than designing and building an advanced sensor that has the power to separate spatial and spectral, so the simultaneous use of spatial and spectral information is certainly not possible without the use of data integration methods.

According to the data presented in Section 5, the proposed method provided a somewhat better combination than the other methods introduced. Also, the point 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.

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