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Application of Modal Brain Imaging Data Fusion Techniques in the Diagnosis of Neurological Disorders

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Abstract: **-** Due to the high incidence and complexity of neurological diseases in clinical medicine, they have a greater impact on the diagnosis and treatment of doctors. This paper firstly analyzes the concept of modal brain imaging data fusion and modal imaging available for fusion, and obtains the types of modal imaging available for fusion. Second, the patient's case information is collected, and the data processing technology is carried out on the collected information to ensure the completeness and clarity of the data. Finally, the feature extraction of the processed data is carried out to obtain the fusion features of the data, and the features are fused together to complete the fusion of modal imaging data. The performance and effect of the modal brain imaging data fusion technique is analyzed from three perspectives: the LGI analysis of patients with neurological disorders, the global network analysis, and the power spectrum analysis of the time series.The LGI values of 3.5 and 3.7 at pain values of 1 and 6 indicate that the intensity of the patient's pain is related to the negative emotions. It was concluded that there is a negative pattern between pain and LGI values and that the characteristic path lengths of patients with neurological disorders and control patients are lower at around 1.05. It proves that the fusion effect of modal imaging is better, which facilitates the diagnosis and treatment of doctors, comprehensively understands the status of patients' diseases, and improves the cure rate of neurological diseases.

Keywords: Neurological diseases; Modal brain imaging; Data fusion; Feature extraction; Global network analysis

1. INTRODUCTION

In the field of medicine, neurological diseases are more complex and diverse among clinical diseases, and it is difficult to carry out targeted treatment for them. In order to better treat neurological diseases, modal brain imaging data fusion technology has been introduced to provide better treatment for patients, so that doctors can have a comprehensive understanding of the patient's condition [1-2]. Modal brain imaging data fusion technology mainly combines the results of different imaging, removes the worthless information, and obtains comprehensive and valuable brain data, which provides doctors with a wealth of information about the patient's disease [3-4]. The application of modal brain imaging data fusion technology can provide better help for the diagnosis of neurological diseases, so that doctors can accurately determine the location and degree of lesions, reduce the possibility of misdiagnosis, help doctors to formulate accurate treatment plans, reduce medical costs, improve the accuracy of disease diagnosis, and has a high practical value [5].

In this paper, firstly, the concept of modal brain imaging data fusion and modal imaging available for fusion are analyzed, and the types of modal imaging that can be used for fusion are derived, including functional magnetic resonance, diffusion tensor, and cerebral metabolic imaging, etc., and the characteristics of modal imaging are

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obtained. Next, case information of patients suffering from neurological diseases is collected, and the collected data are processed to ensure the clarity and completeness of the data to avoid subsequent impact on the performance of the technique. Finally, the processed data fusion features are extracted, and the features are fused together to realize the fusion of modal imaging data. In this way, the patient's brain information can be comprehensively obtained, which facilitates the subsequent diagnosis of the doctor, provides a good treatment environment for the patient, reduces the probability of error, removes the disease in the patient's body, ensures that the patient can live a healthy life, and improves the patient's quality of life.

2. RELATED WORKS

In using modal brain imaging data fusion technique to diagnose diseases, Zhang, Y. et al. firstly utilized local polar map guided filter to turn the source image into iteratively smoothed state. Secondly, the bright feature maps of the source image and multiple scales of the base image were fused using the elemental maximum fusion rule, and the dark feature maps in the source image were fused using the minimum fusion rule. Finally, the fused light feature maps, dark feature maps and the base image are integrated together to generate the patient's brain image, so as to diagnose the patient's disease [6]. Cheng, D. et al. proposed a self-supervised learning model for modal shift in brain imaging, which constructs multi-branching inputs to enable the model to learn the diversity of features of multi-modal data, and by creating an auxiliary task to mine from large-scale unsupervised image data, the model is able to learn the features of multi-modal data. large-scale unsupervised image data to mine supervisory information, in order to build a supervisory information training network, which ensures the similarity between the modal image input and output, and also makes the generated images clearer for patient diagnosis [7]. Zhang, G. et al. integrated deep residual learning and multimodal image features with each other, and extracted and fused the different and complementary features from various modalities using the The multimodal information in deep convolutional neural network improves the clarity of brain images and produces brain images, and according to the experimental test, it is proved that the images produced by this method are clearer, and it can assist the doctors in treating the patients [8]. Tan, W. et al. firstly established a MLEPF model based on weighted mean curvature filtering and decomposed multimodal medical images into three parts: fine structure, coarse structure and base structure. Secondly, the FS and CS layers were fused using a gradient domain pulse coupled neural network fusion strategy, and the BS layers were combined using an energy attribute fusion strategy. Finally, the fused image is obtained by combining the fusion layers to achieve the diagnosis of neurological diseases [9]. Translated with www.DeepL.com/Translator (free version)Zhu, X. et al. firstly recovered the deformed part of the image using GAN, and then directly aligned the image using GAN, which uses the image generated by the improved modal-independent neighborhood as input and the predicted structure of the registered image as output. Secondly, the GAN utilizes the generated structure to align the intensity of the image, and the GAN is trained using different loss functions related to mean square error and least squares loss to generate the brain image of a patient with neurological disease [10]. Jiang, X. et al. proposed a combination of free deformation and symmetric constraints based generative adversarial network as a model for image alignment. The model takes the structures of principal component-based reference image and floating image as inputs and uses a generator to learn the parameters of the model to generate two deformation fields. At the same time, the model uses a discriminator to determine whether bilateral registration is realized simultaneously and whether the obtained images are comprehensively clear [11]. Meng, C. et al. firstly decomposed the multimodal brain MRI images by the established fusion model to obtain the high-frequency component and the energy layer in the images. Secondly, the corresponding energy layer image and high frequency component were fused, and the inverse NSST transformed the energy layer fusion image and high frequency fusion image to obtain the final fusion image. Finally, the obtained images are tested according to the experiment, and the results show that the obtained images are clearer and can complete the diagnosis of the patient [12].

3. MODAL BRAIN IMAGING DATA FUSION TECHNIQUES

3.1 Modal Brain Imaging Data Fusion Techniques

When treating patients suffering from neurological diseases, modality imaging is needed to show the patient's brain condition because of the differences in the equipment and principles of brain imaging. Modal imaging can be divided into anatomical imaging, which includes CT, MRI, and ultrasound, and functional imaging, which includes diffusion tensor imaging, perfusion imaging, and magnetic resonance waveform analysis. Different modality imaging results provide different information and yield different diagnostic results, in order to be able to comprehensively diagnose the patient's disease, the modality imaging data are fused together, so as to understand the patient's disease status and formulate a reasonable treatment plan [13-14].

The data fusion of modal imaging refers to the fusion of the patient's imaging data, the use of computer technology to carry out digital processing of imaging data, each modal imaging to complement each other, forming a new impact information, so as to achieve the purpose of treatment and diagnosis of patients. Imaging data fusion is not a simple superposition of information, but the removal of useless information, will be useful information combined together, helping doctors to develop a reasonable treatment plan, assisting doctors to carry out treatment of patients.

In the current medical field, there are many software to realize imaging data fusion, such as DTI, iplan and SPM, and there are many ways of fusion. The main methods are 3D display method and tomographic display method, in which the tomographic display method is to fuse the obtained imaging results and synchronize the fused data with cross-sectional and coronal display, which is convenient for diagnosis of the patient. The three-dimensional display method is to display the fused imaging data in a three-dimensional way, which assists doctors in making reasonable diagnosis for patients and provides a new direction for curing neurological diseases.

3.2 Modal Brain Imaging Techniques that Can be Fused

In the medical field, there are more modal techniques that can be fused, which are mainly divided into three kinds, functional magnetic resonance, diffusion tensor imaging, and brain metabolic imaging, as shown below:

(1) In the medical field, the imaging mode of functional resonance is usually used when measuring the blood oxygen level, especially for patients suffering from neurological diseases, there are more aerobic hemoglobin and deoxyhemoglobin in the brain tissue. Deoxyhemoglobin contains a magnetic sensitivity effect that reduces the signal in brain tissue. While aerobic hemoglobin does not produce magnetic sensitivity effect, so the two will form a signal ratio in the brain. Therefore, the use of functional magnetic resonance in the form of imaging,

as a way to avoid damage to the nerves of the brain, can clearly reflect the patient's brain, to facilitate the diagnosis and treatment of doctors [15-16].

(2) Diffusion tensor imaging technology is the use of bipolar magnetic field gradient pulses to encode the diffusion movement of water molecules, and the imaging results of the brain are obtained. In the human body, water molecules have two forms of diffusion, anisotropic and isotropic diffusion. The diffusion of water molecules in pure water is usually random, with the same diffusion capacity and a spherical diffusion trajectory. In contrast, water molecules in the brain are hindered by nerve fibers, and the water molecules can only move like the direction of low resistance, and the trajectory is ellipsoidal. Therefore, it is necessary to use diffusion tensor imaging, according to the characteristics of neurology, following the effective tensor direction of each voxel continuous tracking, visualizing the spatial structure and extension orientation of the brain. In this way, the brain condition of the patient is obtained, which facilitates subsequent diagnosis and treatment.

(3) Brain metabolic imaging is a way to understand the metabolic condition of the patient's brain, which usually requires the use of amino acid-based imaging agents, and is used to reflect the location and state of the disease in the patient's brain, and to assist the doctor in formulating a treatment plan.

4. DATA FUSION FOR MODAL IMAGING

4.1 Data Acquisition and Processing

4.1.1 Data acquisition

Patients suffering from neurological disorders were selected for the study, case information and hospitalization of these patients were collected and the brain of the patients was examined using the following brain scanning instruments and the parameters of the scanning are shown in Table 1. The details are as follows:

(1) fMRI instrument, during the examination of the patient's brain, the patient needs to keep both eyes open and stare at the cross sign above, so as to ensure that the patient is conscious during the scanning process. The resting state scan was performed for about 8 minutes at 2-second intervals, with a total of 240 time-point images. Using the anterior-posterior continuous suture line as a reference, the specific scanning parameters were a TR of 2000 ms, a matrix size of 64 × 64, a 90-degree flip angle, a layer thickness of 4 mm, a layer spacing of 0.6 mm, and a voxel size of 3.44 mm × 3.44 mm × 4.60 mm.

(2) dMRI instrument, where the patient was examined for approximately 10 minutes, with the same four sites, with specific parameters of FOV of 256 mm2, matrix size of 128 × 128, 50 slices in total, layer spacing of 0 mm, voxel size of 2 mm × 2 mm × 3 mm, TR of 7,000 milliseconds, and 90-degree flip angle [17-18].

(3) The sMRI instrument, utilizing the acquisition of a multi-echo MPRAGE sequence, with specific scanning parameters of TR of 2530 ms, TE of 3.44 ms, matrix size of 256 × 256 × 192, 7-degree flip angle, FOV of 256 square millimeters, layer thickness of 1 mm, layer spacing of 0 mm, and voxel size of 1 cubic millimeter.

Table 1 Scanning Parameters

Site			**Site 1**	**Site 2**	**Site 3**	**Site 4**
Scanner Type	Supplier		Siemens			
	Model		Trio			Verio
Scan parameters	fMRI	Sequence	2000			
		TR	30			
		TE	240			
		Time	64×64			
		Layer thickness	4			
	dMRI	TR	7000			8400
		TE	92		91	
		Layer distance	0			
		Matrix size	128×128			
		Voxel size	2×2×3			
		FOV	256			
	sMRI	Voxel size	1			
		FA	7			
		Layer thickness	1			
		Layer distance	0			
		FOV	256			
		Direction	Sagittal			

4.1.2 Data processing

After acquiring data using the instrument, the data need to be processed as a way to improve the clarity and completeness of the data, and for the data in fMRI, the specific steps are as follows:

(1) In order to balance the magnetic field and allow the patient to adapt to the time of the examination, the images of the first 10 time points were eliminated, leaving 230 time points in the brain volume.

(2) Time correction, since the acquired slices were not consistent in time, the intermediate slices were used as a reference to correct the images of the remaining 230 time points as a means of correcting for the differences in acquisition time across slices.

(3) In order to avoid the noise generated by head motion affecting the signal, a head-motion correction algorithm was used to estimate six parameters including the translational positions in the x, y, and z directions,

and the rotation angles around these three directions.

For dMRI data, data processing first requires quality checking, and for each image of the patient, a screening process is initiated to remove any images that show excessive head motion as well as vibration artifacts in any gradient direction. Next, eddy current correction aligns all diffusion-weighted images into non-diffusion-weighted images and is used to correct for the effects of eddy current distortion and head movement. Subsequently, a gradient direction correction was performed, where the head motion correction in the previous step was accompanied by a gradient direction unfolding correction for each image. Finally, the diffusion tensor as well as scalar metrics such as FA, MD, etc. were calculated.

For sMRI data, the data processing process starts with the alignment of the original 3D image to the standard space. The brain volume is segmented into gray matter, white matter, and cerebrospinal fluid by a priori probability and image grayscale information. Then the modulation correction space alignment is used to cause the brain volume to change, and finally the gray matter image obtained from the image segmentation of the examined patient is spatially smoothed by using the homogeneous 8 mm Gaussian nuclear high-frequency physiological respiration and cardiac noise signals to improve the signal-to-noise ratio.

4.2 Data Fusion Process for Modal Imaging

4.2.1 Feature extraction

After launching the preprocessing of sMRI, dMRI data and fMRI data, the features of modal fusion, gray matter volume and FA can be obtained for sMRI and dMRI data, but the fMRI data need feature extraction to obtain the corresponding features, so it is necessary to launch the feature extraction for the fMRI data, the specific process is as follows:

(1) PCA dimensionality reduction, using principal component analysis method to unfold dimensionality reduction of preprocessed fMRI data. fMRI data are dimensionalized into 100 principal components because choosing higher order model will appear more fine components [19-20].

(2) Group ICA decomposition, using the Infomax algorithm within the GIFT toolkit to carry out group ICA decomposition of fMRI data, repeatedly using the Infomax algorithm for 20 times, and then aggregating the obtained data using the clustering method, so as to make the component decomposition become more stable.

(3) Back-reconstruction, the GICA3 post-reconstruction method using PCA approximation and projection is used to estimate the spatial maps and time series. Among other things, the GICA3 algorithm contains features not available in other algorithms, like a random effects model that distributes the obtained inspection imaging effects zero-mean around the group average effect [21].

(4) ICNs component selection, the components are selected by the decision criteria as the intrinsic network for fusion, when the components are decomposed using the group ICA technique. Blind source separation is usually chosen to decompose it into many components, and then obvious physiological artifacts are removed. The selection of components utilizing ICNs is mainly divided into two parts, the first is to examine the image and TCs power characteristics in the total space, from which the components are initially selected, which usually contain TCs low frequency oscillations, low artifact overlap, and TCs power with low spectral power, and so on.

Secondly, the network is divided into subcutaneous, auditory, visual, default and sensorimotor networks, etc., using the activation zone coordinates of the selected independent components.

(5) Post-ICA processing, in the examined imaging images selected as ICNs do remove covariate processing components, including de-drift, regression of six head movement parameters, de-spiking, and low-pass filtering, in which the value of low-pass filtering should be less than 0.15 Hz, etc.

(6) FNC matrix calculation, the TCs of the examined imaging images are processed by post-ICA, and the Pearson's correlation of the ICNs components is calculated after processing to generate an FNC matrix.

4.2.2 Fusion of modal imaging data

The modal fusion method based on 4-way mCCA+jICA is used to expand the features of the imaging data to be fused with each other, the blind source separation model is used to complement the advantages of CCA and ICA, and the mCCA is used to find the flexible connection between the features of the imaging data, and the jICA is used to more accurately separate the source components to obtain the common mixing coefficients, and the process of fusion of the modal imaging data is shown in Fig. 1. The basic strategies of modal imaging data fusion are mainly as follows:

(1) Extract the four features ReHo, FNC, FA, and GM from the three modalities of fMRI, dMRI, and sMRI, respectively, using the mCCA approach, and project them into the same space to maximize the mixing coefficient correlation of the features.

(2) The correlation maps obtained by the mCCA method are connected using a series connection, thus generating a cascade map.

(3) The jICA method is applied to the cascade map to obtain the final independent source components and the corresponding mixing coefficients, thus completing the fusion of modal imaging data.

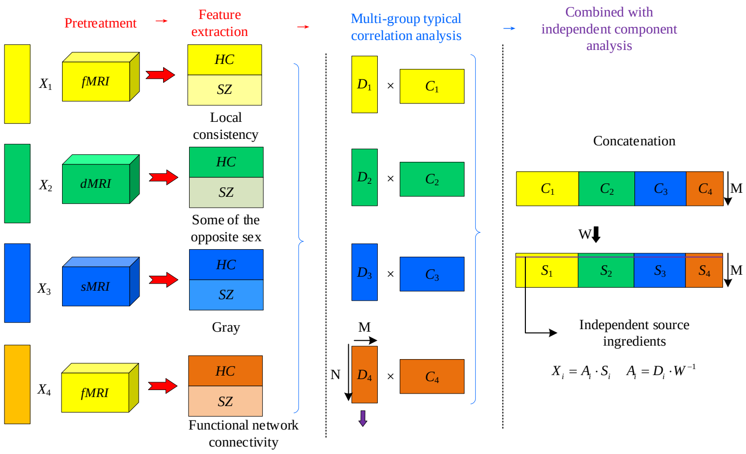

Figure 1 Modal Imaging Data Fusion Process

5. APPLICATION ANALYSIS OF MODAL BRAIN IMAGING FUSION TECHNIQUES

5.1 Experimental Preparation

In order to be able to more intuitively see the performance and effect of modal brain imaging data fusion technology, patients suffering from neurological diseases were selected as research subjects and their information and clinical data were collected, and the clinical information of the patients is shown in Table 2. The scanner was used to scan the brain condition of the patients, and the parameters of the scan were set as repetition time = 1900 ms, inversion time = 900 ms, callback time = 2.52 ms, flip angle = 9°, number of layers = 176, resolution = 1 × 1 × 1 cubic millimeter, and matrix = 256 × 256, so as to obtain the brain condition of the patients.

Table 2 Clinical Information of Patients

Sample	Patients with neurological diseases	Normal control
Number of studies	20	20
Gender (male/female)	15/5	15/5
Age (years)	56±11.75	55±9.69
Disease duration (years)	6.25±5.89w	None
Pain severity (NPRS)	2.30±1.41w	None
Pain location (V1/V2/V3)	0/10/10	None
Affected side (left/right)	7/13	None
Medications taken (CBZ/GBP&GBP)	16/1/3	None

5.2 LGI Analysis of Patients with Neurological Disorders

The human brain structure is usually very plastic and can adapt or not adapt to long-term injury inputs, so many neurological disorders of the brain occur frequently. In order to enable better treatment, modal imaging data fusion is used as a way to better analyze the patient's brain condition, and the LGI analysis of the patient is obtained using modal imaging data fusion, and Figure 2 shows the results of the LGI analysis. The modal imaging data fusion technique can clearly show the patient's disease condition, and it can be concluded that the LGI value of the left insula region of patients with neurological diseases is lower than that of the normal control, and the trend of negative correlation between the patient's pain intensity and the average LGI value of the insula region. At a pain value of 1, the LGI value was 3.7, and at a pain value of 6, the LGI value was 3.5, indicating that the intensity of pain in patients is related to negative emotions. When patients experience conditions such as anxiety and sadness, the pain in the brain appears to intensify, which is not suitable for neurological disorders. The use of modal imaging fusion data technology to show the patient's brain condition comprehensively facilitates the doctor to start the treatment of the patient's disease, formulate a reasonable clinical treatment plan, reduce the patient's pain level, improve the patient's life treatment, prolong the patient's life, and provide a new direction for the treatment of neurological diseases.

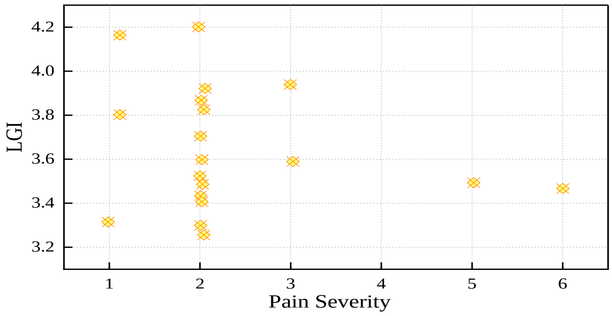

Figure 2 LGI Analysis Results

5.3 Global Network Property Analysis

Global network attribute analysis is an important criterion used to evaluate brain structure and function as a means of revealing the extent and effectiveness of imaging fusion techniques. Among the global network attributes, the criteria for the small-world attribute are the clustering coefficient less than 1 and the standardized feature path length approximately equal to 1. Whereas the brain networks of patients with neurological disorders and the normal control group both show the small-world attribute, the global network analysis is unfolded for the patients with neurological disorders and the normal control group in Fig. 3. The characteristic path lengths, clustering coefficients, and small-world scalars for the two groups, respectively, where the normal control group utilizes the NC representation and the patients with neurological diseases take the PC representation. The difference between the clustering coefficient, standardized eigenpath length and small world scalar for the two groups, analyzing the difference between the two at 95% confidence interval shows that there is no significant difference between the clustering coefficient, standardized eigenpath length and small world scalar between neurological disease patients and normal controls, and that eigenpath lengths of neurological disease patients and control patients are lower at around 1.05. It proves that the fusion effect of modal imaging is better, which can comprehensively show the condition of the patient's brain and facilitate the subsequent diagnosis and treatment.

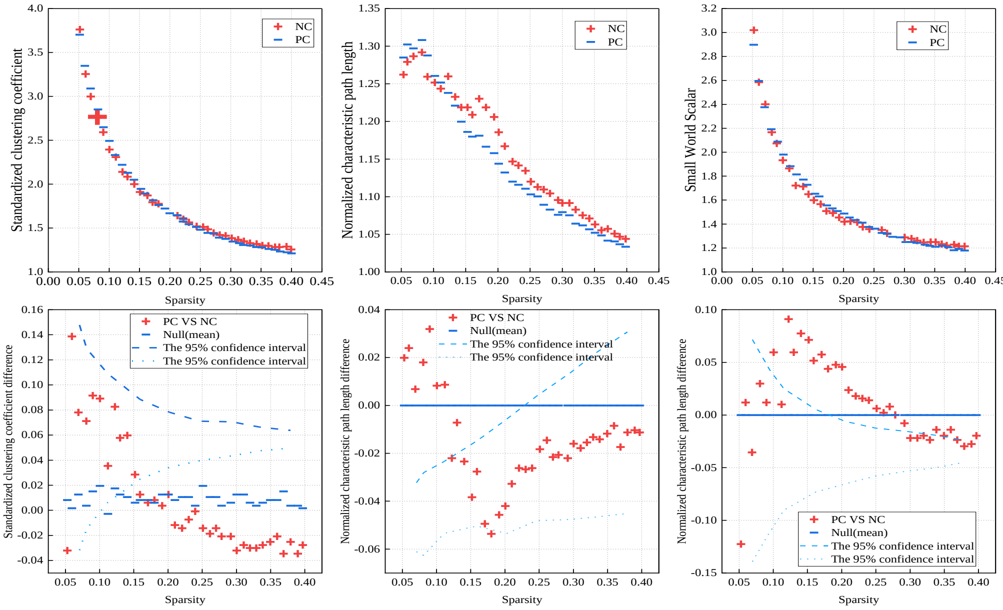

Figure 3 Global network analysis

5.4 Power Spectrum Analysis of Time Series

The power spectrum analysis of time series is mainly to analyze the frequency components in the time data series, which can be used to analyze the temporal correlation in the fusion data, evaluate whether the modal brain imaging data fusion technology can better show the structure and characteristics of the brain, so as to better assist the doctor in diagnosing the patient, and come up with a specific treatment plan to improve the accuracy and effect of the treatment, so the modal brain imaging data fusion technology can be used to analyze the frequency components in the time series. Therefore, the modal brain imaging data fusion technique is used to analyze the power spectrum of the time series, and Table 3 shows the power spectrum analysis of the time series. The energy is mainly distributed in the low-frequency band of less than 0.1 Hz, with the peaks in 0.015 Hz in the normal group and 0.011 Hz and 0.043 Hz in the patient group, and in the substantia nigra of the brain bilaterally, the T-values of the patient and the control group are 5.45 and 5.30. In the amygdala of the brain bilaterally, the T-values of the patient and the control group are 7.97 and 14.19, and in the hippocampus and paraganglios of the brain bilaterally, the T-values of the patient and the control group are 7.97 and 14.19. In the parahippocampal gyrus, the T-values of the patients and the control group were 7.15 and 10.26. This shows that the spectral changes obtained by the brain nerves yielded information about the patients' brains, which facilitates the diagnosis and treatment of doctors, and enables them to formulate a reasonable treatment plan and reduce the recurrence rate of the disease. At the same time, it enhances the cure rate of the disease, ensures the health of the human body from being troubled by the disease, and provides a new direction and way for the treatment of neurological diseases.

Table 3 Power spectrum analysis of time series

Brain Region	**Talairach coordinates**			**T-value**
	X	Y	Z	
Patient group > control group				
Substantia nigra (bilateral)	-12	-18	-5	5.45
	15	-24	-9	5.30
Globus pallidus (bilateral)	-16	5	1	8.55
	15	5	5	7.03
Putamen (bilateral)	-18	6	10	7.64
	15	6	0	8.70
Hypothalamic nucleus (bilateral)	-11	-19	-3	4.21
	12	-17	-5	5.16
Caudate nucleus (bilateral)	-12	19	-6	9.78
	15	22	-6	7.97
Amygdala (bilateral)	-24	1	-18	14.19
	24	-8	-18	8.90
Parahippocampal gyrus (bilateral)	-18	-5	-20	7.15
	15	4	-18	10.26

Patient group<control group				
Cerebellum (bilateral)	-33	-42	-42	6.37
	30	-39	-34	5.48

6. CONCLUSION

This paper analyzes the concept of modal brain imaging data fusion and modal imaging available for fusion to obtain the types of modal imaging available for fusion. The modal imaging data fusion is accomplished by collecting the patient's information and performing data processing techniques on the collected information to extract the fusion features of the processed data. In order to be able to study the performance of modal brain imaging data fusion in depth, and to analyze the ability and level of modal brain imaging data fusion technology, it was found that the modal brain imaging data fusion technology can clearly show the situation of the patient's brain, and can analyze the patient's pain and mood related to the analysis of the 95% confidence interval yielded a characteristic path length of neurological disease patients and the control group patients is lower at around 1.05 . In the location of the amygdala in the brain bilaterally, and in the location of the parahippocampal gyrus in the brain bilaterally, the T-values of the patients and the control group were 7.97 and 14.19, 7.15 and 10.26, which proved that the fusion of modal imaging is more effective, and it can assist the doctors in the treatment of the patients suffering from neurological disorders, and formulate a reasonable clinical plan, so as to clear the disease in the patient's body, which can help to improve the quality of life of the patients and prolong the life of the patients. It can help to improve the quality of life and prolong the life span of patients.

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