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The AR and ARFI-Based Models Utility of Magnetoencephalography Assisted Diagnosis of Depression

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Abstract: *This paper is an attempt to distinguish depressed patients from healthy samples mainly by analyzing magnetoencephalogram data of depressed patients and healthy people under different emotional picture stimuli. The following conclusions are mainly drawn: First, the relationship of information storage and condition entropy is obtained firstly through the formula derivation, and the higher the information storage value, the lower the condition entropy. The healthier the biological system, the higher the complexity. Second, the conditional entropy values of the magnetoencephalography channel were mostly higher in the healthy samples than in the depressed patients under the emotional picture stimulation. Accordingly, the conditional entropy values of the frontal region under negative stimulation were lower in depressed patients than in healthy subjects. Third, under both the AR model and the ARFI model, the magnetoencephalogram information storage values were higher in depressed patients than in healthy samples. The difference was more pronounced especially near the frontal regions for both. The variability of the results obtained under the ARFI model was even more pronounced when depressed patients and healthy samples were more discriminated near the left frontal region than the right frontal region, as revealed by the study of line plots of information storage values across left and right frontal regions channels.*

Keywords: *Depression; ARFI; MEG; Conditional Entropy; AR*

1. Introduction

Depression pathogenesis is complex, and current medical diagnostic means are single. Major depressive patients even experience huge body pain as well as suicidal tendencies and so on. Therefore, it is particularly important to discover methods that can effectively treat depression, according to the survey: the incidence of depression in our country is 3.8% - 5.7%, but the identification rate of depression is still less than 20%, and only less than 10% of depressed patients have received relevant pharmacological treatments.[1-4] MEG can superimpose the location of analyzed intracerebral activity on anatomical images such as MRI (magnetic resonance imaging) to provide the structure and function of the brain. As an important basis for clinical diagnosis and treatment, MEG has received significant attention from many countries and scientists. MEG can effectively analyze the behavior and emotions of patients by detecting physiological information in various brain regions of the human brain. Currently, many emotion related diseases have been effectively prevented, treated, and restored by the detection of MEG. Magnetoencephalography is a new direction for the study of brain function, and it is important to determine whether the complexity is perfect, so it is crucial to choose appropriate methods to analyze the complexity of magnetoencephalography, and entropy algorithms are among the most powerful methods for calculating the complexity of brain function, such as permutation entropy and approximate entropy. Therefore, at present, domestic and extrinsic methods are mostly used to solve when analyzing nonlinear signals such as magnetoencephalography and EEG.[5-7]

At present, the study of event-related magnetic field changes depression magnetoencephalography mainly includes two aspects of physical sensory irritation and cognitive ability. For the resting state of depression research is mainly dominated by slow waves generated by neural activity in brain regions, previous studies have found that the generation of slow waves is mainly due to Neuro-Electromagnetic

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changes in brain regions and thus leads to slow wave activity near the corresponding brain regions, for which many foreign experts deeply study, Brigitte et al, first selecting some patients with schizophrenia and depression or patients with affective disorders and then contrasting the slow wave changes in normal human brain regions, found that the affective disorders in patients with psychiatric disorders may be caused by abnormal slow wave activity in the frontal lobes. Christian et al showed that frontal slow wave activity was significantly reduced in depressed patients relative to schizophrenia patients and normals, and that slow wave activity in the temporal and parietal lobes of depressed brains was also reduced relative to schizophrenia patients, such that the density of dipoles corresponding to slow waves in brain regions was reduced in depressed patients, particularly relative to schizophrenia patients, The percentage of dipoles in depressed patients was significantly reduced in whole brain regions, and finally it was found that depressed patients showed significant differences relative to normal controls only in frontal regions; Through further studies of the abnormal slow wave activity in these brain regions, it was found that all were related to clinical target symptoms, such as patients with essence schisis hallucination was associated with increased slow wave activity in the left temporal lobe of the brain, depression related symptoms were associated with decreased slow wave activity in the left frontal lobe of the brain.[8] Another similar study found abnormalities in slow wave activity in the right occipital region of the brain if depressed patients were left untreated, such that the dipole density of slow waves in the occipital region increased which could be an element of depression generation.[9-11]

This paper mainly applies AR and ARFI models to analyze the information storage differences of magnetoencephalograms from healthy individuals and depressed patients by employing multiscale conditional entropy methods to analyze the differences in brain complexity between healthy individuals and depressed patients.

2. Methods

2.1. Dataset description and preprocessing

The magnetoencephalogram data acquired in this experiment were distributed in 5 different brain regions, 5 being occipital (occipital, O), frontal (frontal, f), central (central, c), temporal (temporal, t), and parietal (parietal, P).[12] However, different brain regions are located in different large regions, including the left, middle, and right regions, which are denoted by L, Z, and R, respectively. The correspondence of different brain regions is shown in figure Fig 1. The CTF 275 holoprosencephaly magnetoencephalography system has 275 information channels, 132 and 11132 in the left, middle, and right regions, respectively. Description: the 275 channels are all composed of three letters and two digits, with the first letter representing the brain magnetic signal, with two letters representing the larger region, that is, the left, middle, and one of the right regions, and with the third letter representing the region, that is, the frontal, occipital, temporal, parietal, and one of the central regions. The latter two numbers represent the coordinates where the channel was located. For example 25 channel expressed as mlf11. 1 ~ 24, 133 ~ 156 channels are located in the central area, 25 ~ 57, 157 ~ 189 channels are located in the frontal area, 58 ~ 76, 190 ~ 208 channels are located in the occipital area, 77 ~ 98, 209 ~ 230 channels are located in the parietal area, 99 ~ 132, 231 ~ 264 channels are located in the temporal area; Above are channels located in large areas and symmetrical to each other, say: 25 ~ 57 in the left frontal area, 157 ~ 189 in the right frontal area, other channels are similar. Both 265 ~ 275 are information channels located in the middle zone.

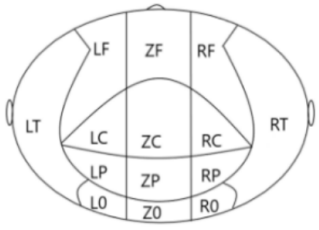

Figure 1: MEG distribution maps of different brain regions

This paper was collected with Data of MEG suffix with a sampling frequency of 1200 Hz. These data are all three-dimensional data of 275*161*80, 275 channels per acquisition, 161 data sampling points, and 80 represents the number of pictures of different emotional stimuli, that is, pictures of positive, moderate, and negative stimuli in this paper. Since Matlab cannot process The MEG form of

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the data, so first the data is transformed into Matlab can identify Data in mat format. This will be taken for subsequent experiments Mat rectangle data.

2.2. Multiscale conditional entropy

Originally proposed by Kolmogorov for the concept of complexity, their measure of complexity focused on describing the random length of sequences, somewhat reflecting the concept of entropy many of our physiological metrics can be measured in terms of complexity. Chaos holds that the higher the complexity of a person's physiological system, the better its stress capabilities are.

At present, common entropy measurement methods have approximate entropy, sample entropy and so on. The approximate entropy and the complexity of the time series are proportional, and the larger the approximate entropy, the more complex the time series, and vice versa. Sample entropy is also a method used to measure temporal complexity and is nothing more than a certain improvement over approximate entropy. Costa proposed a multiscale entropy algorithm. Multiscale entropy (MSE) extends the sample entropy to multiple time scales, which offers the following advantages:

① It is suitable for analyzing systematic time series;

② Information of the original signal can be effectively restored. The problem with sample entropy is that it does not account well for the different timescales that may exist in a time series. The basic principles of multiscale entropy include coarse granulation or downsampling of time series, mostly to analyze time series at increasingly coarse temporal resolutions.

Conditional entropy represents the degree of irregularity in the time series of a nonlinear dynamic system and can be used to characterize the complexity of the system. On the basis of conditional entropy plus multiscale treatment forms the experimental approach of this chapter: multiscale conditional entropy. It mainly starts with a coarse-grained time series, then a coarse-grained sequence is subjected to phase space reconstruction, and finally the conditional entropy of the sequence is calculated. It is critical to combine multiscale and conditional entropy, which can over come averages after serial segmentations that can in turn compose a new time series. This makes it possible to study the complexity information inherent to each period of the time series separately, without making calculations on the entire time series, improving computational efficiency. Attention needs to be paid in multiscale algorithms to the choice of scale factor in the coarsening process, and the size of scale factor is directly related to whether it can accurately extract the information of time series and distinguish the difference between time series. The sequence also needs phase space reconstruction after it undergoes coarse-grained process, and the key of phase space reconstruction is the selection of embedding dimension parameters and determination of the optimal time delay.

2.3. Selected scale factors

It is important to choose an appropriate scale factor in order not to affect the experimental results. To be representative of the last data obtained, our final data were all post averaged, first by calculating and then averaging the multiscale condition entropy over 10 healthy experimenters, and second by calculating and then averaging the multiscale condition entropy over 6 depressed patients. The obtained results were analyzed according to different scale factors, and the most appropriate scale factor was selected. Below are plots of the change in the multiscale conditional entropy between depressed patients and healthy subjects in the face of stimuli from positive emotional pictures, and since the scale factors should not be too large or too small, 4, 6, 8 were chosen for this experiment scale factors were sequentially replaced for comparison. The abscissa represents 275 informative channels of the magnetoencephalogram, and the ordinate is the multiscale conditional entropy value of the experimental subject.

2.4. AR model and parameter selection

The AR model belongs to the random signal parameter model and is also a type of linear output model. The model can be expressed in the following equation:

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$$x(n) = \sum_{i=2}^{p+1} a_i m(n-i+1) + \omega(n) \tag{1}$$

In the above formula, $x(n)$ is time series of MEG signals, a_i is the prediction coefficients of the AR model, p is the order of the model and $\omega(n)$ is the prediction error. In this study, AR model parameter estimation was performed by least square method, the choice of the order p is crucial in the modeling process. Defining filtered data $X_n^{(f)} = X_n$. Finally ordinary least squares was used to extract the data from the filtered $X_n^{(f)}$ to estimate the AR parameters, to solve the AR model $A(L)X_n^{(f)} = E_n$. The order p of the model was evaluated by Bayesian information criterion. Finally it was chosen as 12 and low pass filter step was chosen as 48 in the experiment.

2.5. ARFI model and parameter selection

ARIMA model (autorepressive integrated moving average model), a differential integrated moving average autoregressive model, also known as integrated moving average autoregressive model (moving also known as slippage), is one of the time series prediction analysis methods. ARIMA (p, d, q), where AR is the " autoregressive " and p is the number of autoregressive terms; MA is the " sliding average ", q is the sliding average term, and d is the number of differences (orders) made to make it a stationary sequence. Although not present in the English name of ARIMA, the term 'difference' is a critical step. The model can be expressed as:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right)\varepsilon_t \tag{2}$$

The ARFI model is stationary at 0.5 <d < 0.5 and nonstationary at 0.5 < d < 1 but implies regression. By allowing d to be written as d = D1 + d > 1 with 0.5 < D1 < 0.5 D and D ∈ {1,2,...}, The ARFI model can be extended to nonstationary settings. The most common situation occurs at d = 1, when the process is called to have a unit root; The ARFI (p, d) formula is then used to model the increment of the series, which is the difference between consecutive observations. Note that the defined process is a special case of the broader ARFIMA (p, d, l) process, which also contains a class of autoregressive processes AR (P). Here we restrict our analysis to the description of the ARFIMA (p, d, 0) process, which we denote as the ARFI (p, d) process.

3. Result and Discussion

3.1. Scale factor selection

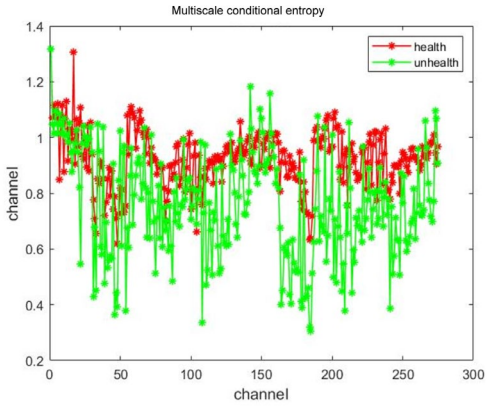

Figure 2: Multiscale conditional entropy with a scaling factor of 4

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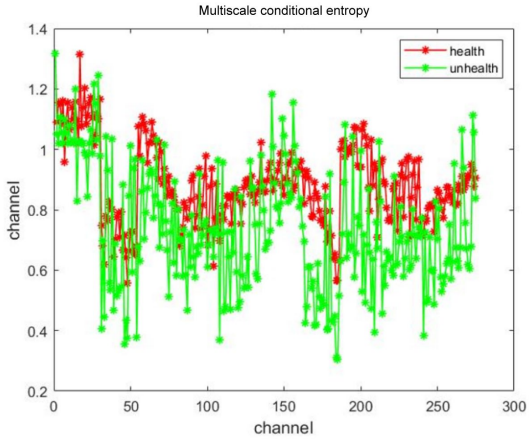

Figure 3: Multiscale conditional entropy with a scaling factor of 6

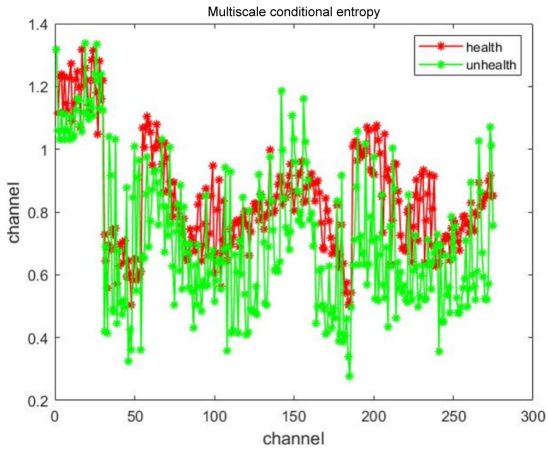

Figure 4: Multiscale conditional entropy with a scaling factor of 8

From the top panel, when the scale factor is 6, the ensemble shows that the multiscale conditional entropy of healthy experimenters is larger than that of depressed patients, also with good discrimination in the left as well as the right frontal regions. So when selecting the scale factor 6, the depressed patients and healthy samples can be relatively well distinguished. The panels below are the MEG information storage profiles of depressed patients and healthy subjects through different emotional stimuli under AR and ARFI models.

3.2. Performance for the two models

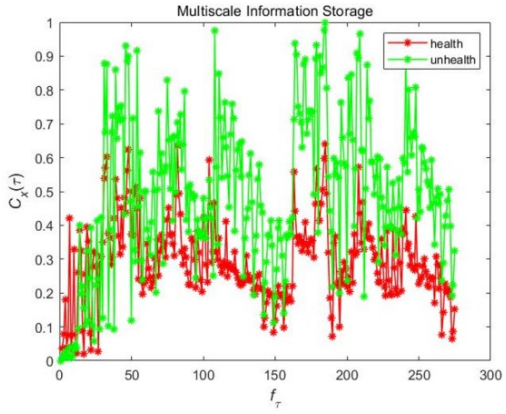

Figure 5: The distribution maps of information storage of brain magnetograms of experimental subjects under the ARFI model

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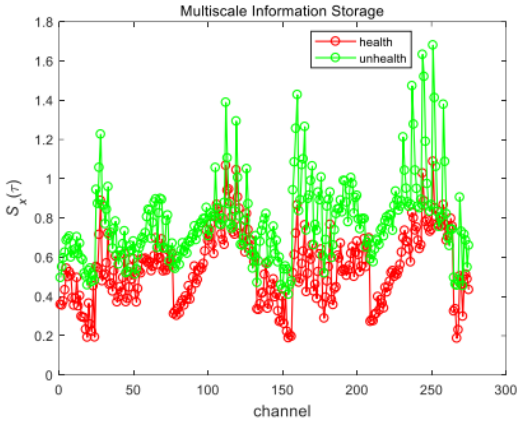

Figure 6: The distribution maps of information storage of brain magnetograms of experimental subjects under the ARFI model

It can be seen from the figure that the information storage values of most channels of the magnetoencephalograms of healthy subjects are smaller than those of patients with depression when facing different emotional picture stimuli, that is, the conditional entropy values of the magnetoencephalogram signals of healthy samples are higher than those of patients with depression under emotional picture stimuli. A study comparing the information storage values of the magnetoencephalography signals under the two models can see that the analysis of the information storage values of depressed patients and healthy people under the same experimental conditions can lead to similar conclusions in both models. But the AR model was less significant in the distribution of magnetoencephalogram information storage in both experiments than the ARFI model in calculating the difference in magnetoencephalogram information storage values between depressed patients and healthy samples. Thus, it appears from experimental results that the ARFI model is more powerful than the AR model in studying magnetoencephalographic information storage experiments of depression.

4. Conclusion

The stress of life and work causes most young people to start becoming depressed and having difficulty falling asleep, and gradually develop depressive symptoms. By analyzing the magnetoencephalography data of depressed patients and healthy individuals under different emotional picture stimuli, we found that the conditional entropy values of the magnetoencephalography channel were mostly higher in healthy samples than in depressed patients under emotional picture stimuli. When subjects were faced with different emotional stimuli, information storage values of magnetoencephalograms were mostly higher in depressed patients than in healthy samples, although the variability of the results obtained under the ARFI model was more obvious.

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