Research on Multiscale Information Storage of MEG of Depression Based on ARFI Model

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ABSTRACT

As a noninvasive brain function detection technique, Magnetoencephalography (MEG) has been widely used in the research of depression. By analyzing the amount of information storage, the difference of MEG information storage between patients with depression and healthy people was studied. Our analysis was carried out in the popular multiscale entropy framework, in which the time series were first "coarse-grained" on the selected time scale by low-pass filtering and down-sampling, and then its complexity was evaluated ac-cording to conditional entropy. Within this framework, we used the linear fractional integral autoregressive (ARFI) model to derive the analytical expression of information storage calculated at multiple time scales. We used the information storage expression derived from the ARFI model and then collected the information storage of MEG through positive, negative and neutral stimuli and finally calculate it. The experimental results showed that it was best to distinguish between patients with depression and healthy people through the information storage of MEG through positive stimuli, and it was best to distinguish healthy people from patients with depression at a higher frequency if it was negative or neutral stimuli.

CCS CONCEPTS

• **Applied computing**; • **Life and medical sciences**; • **Bioinformatics**;

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KEYWORDS

Magnetoencephalography, Fractional Integral Autoregressive, Information Storage, Depression

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1 INTRODUCTION

According to the Global Disease burden Survey, the functional disability caused by major depression will be second only to ischemic cardiomyopathy by 2020. Therefore, we should pay attention to the treatment of depression. Psychological intervention plays an important role in the treatment of depression. At present, the number of patients with depression in China has reached 30 million. By 2020, depression will become the second largest disease in China after cardiovascular disease. Patients with depression are mainly characterized by emotional suppression, so they also show emotional disorders. Depression refers to some kind of unpleasant mood and disorder of certain physical organs, which can range from mild sadness to severe despair [1]. Therefore, it is particularly important to find effective methods to treat depression. According to the survey, the incidence of depression in China is 3.8%-5.7%.

At present, the number of patients has exceeded 30 million. However, the recognition rate of depression is less than 20%, and less than 10% of patients with depression have received the relevant drug treatment [2]. It's not only because of the patients' own reasons, but also technical problems. After consulting the data, it is known that MEG is used to study the magnetic signals of brain tissue, and it can accurately consulting provide the functional information electrophysiology of brain tissue in space and time. It is the only noninvasive method to detect the intracellular activity of brain tissue [3]. MEG is a noninvasive neurophysiological technique that

measures the spatial distribution of the magnetic field generated by the neural activity of the brain. The spatial distribution of the magnetic field is analyzed, the source of brain activity is analyzed, and the location of the source is superimposed on anatomical images such as MRI to provide the structure and function of the brain. The main features of MEG are as follows: First, MEG is a detection method that can easily measure brain function. Because MEG signals are recorded on the scalp by the synchronized activities of thousands of neurons. Second, MEG has a high time resolution, and event measurement can be measured in milliseconds. Third, MEG has good spatial resolution. When positioning the signal source, its accuracy can be accurate to the millimeter level, which is a very prominent advantage. Fourth, MEG is completely noninvasive. Because the system does not need to inject isotopes or x-rays during detection, no side effects on the human body have been found so far. Therefore, MEG can be used as an important basis for clinical diagnosis and treatment, and it has been paid attention to by many countries and scientists. MEG can effectively analyze the behavior and emotion of patients by detecting the physiological information of various brain regions. At present, through the detection of MEG, many emotion-related diseases have been effectively pre-vented, treated and recovered. The complexity of human signal activity reflects the characteristics of human physiology in nonlinear dynamics, and the change of its complexity can reflect the change of human body symptoms. In this paper, multiscale conditional entropy is used to judge the complexity. Multi-scale is to coarse-grained time series in order to better extract the relevant information of the signal. It is beneficial to the study of the related pathological mechanism information in the magnetic map signal of depression. This paper mainly studied the difference of MEG information storage between patients with depression and healthy people. We implemented the ARFI model, which could be used to calculate the analytical expression of information storage in multiple time scales. So that we could compare the difference of MEG information storage between healthy people and depressed patients.

2 ALGORITHM INTRODUCTION

This part mainly introduces the algorithm used in the article.

2.1 ARFI Model

Let's know about what the ARFI model is, and the ARFI process takes the form:

$$A(L)(1-L)^{d}X_{n} = E_{n} \tag{1}$$

First, suppose a zero-mean stochastic process X_n, $-\infty < n < +\infty$. Then as a fractional integral autoregressive (ARFI) process, it is provided by an unrelated innovation En supplier. Where L is the backward shift operator ($L^{x}X_{n} = X_{n-x}$), $A(L) = 1-\sum_{x=1}^{r} A_{x}L^{x}$ is an autoregressive(AR) polynomial of order r. $(1-L)^{d}$ is a fractional difference operator defined by [4]. The ARFI model is stationary at $0.5 < d < 0.5$ and non-stationary at $0.5 < d < 1$, but it means regression. From this we can see the relationship between the integral autoregressive model and the autoregressive model. In fact, both of them belong to the special cases of the fractional integral moving average autoregressive model ARFIMA [5]. First, we know that the fractional integral moving average autoregressive model is in the form of AFRIMA(r,d,l), and then ARFI is a case of ARFIMA(r,d,0), AR(r) is a case of ARFIMA(r,0,0). Hosking(1981) introduced the ARFIMA model, which can overcome the weakness of ARIMA model, ARIMA can only explain short-term time series, while ARFIMA can explain short-term and long-term time series So let's go on to look at the parameters of the ARFI model (1), that is, the coefficient of A(L) and the variance of innovation E, which are obtained through a finite length process. First, the differential parameter d is estimated by the Whittle semiparametric local estimator, and then the filtered data is defined:$A(L)X(f)^{n} = E_{n}$, Finally, the ordinary least square method is used to estimate the AR parameters from the filtered data $X(f)^{n}$ to solve the AR model.

2.2 Information Storage

We first define the X_n random variable to describe the current state the system, and define the infinite dimensional vector variable that describes its past state as $X_{n}^{-} = X_{n-1}X_{n-2}\ldots$

The information stored in the system is defined as:

$$S_X = I(X_n; X_n{}^{-}) = E[\log \frac{p(x_n, x_{n-1}, \ldots)}{p(x_n)\,p(x_{n-1}, x_{n-2}, \ldots)}] \tag{2}$$

$I(\cdot;\cdot)$ represents mutual information, $p(\cdot)$ represents prob-ability density function. According to the information theory, the information storage of the system is also related to the entropy of the system, and there are the following formulas:

$$S_{x} = H(X_{n}) - H(X_{n}|X_{n}^{-}) = H(X_{n}) - C_{x} \tag{3}$$

$H(X_n)$ represent the entropy of the current system, $H(X_n|X_n^{-})$represents conditional entropy. Even if the conditional entropy is simplified, it can not reliably perform the multiscale calculation of conditional entropy in a long time range. Here, in order to overcome these limitations, we limit the analysis to the Gaussian process and derive the exact expressions of conditional entropy and information storage for this process. Specifically, we use the relation described in (3) and turn it into a linear system, which can be fully described by the ARFI dynamic process in the form of (1). Specifically, we notice that given ARFI representation, the entropy of the current state of the process and the conditional entropy of the given past state can be expressed analytically and innovatively according to the variance of the X_n, Σ_x process, and the information storage formula is obtained as follows:

$$H(X_{n}) = \frac{1}{2}\ln 2\pi e\Sigma_{X} \tag{4}$$

$$H(X_{n}|X_{n}^{-}) = \frac{1}{2}\ln 2\pi e\Sigma_{E} \tag{5}$$

$$Sx = \frac{1}{2}\ln\frac{\Sigma_{X}}{\Sigma_{E}} \tag{6}$$

Below we will extend (6) to the case of multiple time scales. Because our research is to calculate the information storage in multiple time scales, so as to calculate the information storage for the stochastic process with ARFI representation. In order to obtain the rescaled version of the stochastic process on the time scale defined by the scale τ factor, the method originally designed in [6] corresponds to simply taking the process average of τ continuous samples. The process was later improved on [7, 8] because it actually included two subsequent steps of filtering the process using a low-pass filter

with a cutoff frequency f$\tau = 1/2\tau$. Then the filtered process is down-sampled using a decimation τ factor. According to this improved method, we first apply the linear finite impulse response (FIR) filter to the original process X_n to obtain the following filtered processes:

$$X_n^{(p)} = Z^{(I)} X_n \tag{7}$$

P is the order of the filter, and $Z^{(I)}$ is the coefficient of the filter. Then, by using the relationship between the ARFI model and the state space equation, we prove that (6) can be expressed in the form of the state space equation as follows:

$$Z_{n+1}^{(p)} = B^{(p)} Z_n^{(p)} + D^{(p)} E_n^{(p)} \tag{8}$$

$$X_n^{(p)} = C^{(p)} Z_n^{(p)} + E_n^{(p)} \tag{9}$$

The down-sampling of our (8) and (9) at the scale factor τ can eventually be transformed i-nto:

$$Z_{n+1}^{(\tau)} = B^{(\tau)} Z_n^{(\tau)} + D^{(\tau)} E_n^{(\tau)} \tag{10}$$

$$X_n^{(\tau)} = C^{(\tau)} Z_n^{(\tau)} + E_n^{(\tau)} \tag{11}$$

It constitutes a rescaled version obtained by filtering the AR approximation of the original ARFI processing (1) and then down-sampling. Among the parameters of the state space model, the parameters related to the calculation of information storage are the variance of the down-sampling process $\Sigma_{X(\tau)}$and the variance of the corresponding innovation$\Sigma_{E(\tau)}$.These differences can be used to generate an expression of stored information similar to (6). In the original processX_n, the information storage expression about τ is obtained when observed at the time scale τ:

$$S_X(t) = \frac{1}{2} \ln \frac{\Sigma_{X(\tau)}}{\Sigma_{E(\tau)}} \tag{12}$$

3 EXPERIMENTAL RESULTS AND ANALYSIS

This chapter mainly introduces the experimental analysis and results.

3.1 Data Analysis

This experiment is a comparative experiment of MEG information storage between healthy people and patients with depression. The depression group is 8 patients with depression admitted to the Affiliated Hospital of Nanjing Medical University. A sample of six depression patients in this experiment was three men and three women, all aged 20-30 years, with an average age of 25±3. Five men and five women were among the 10 health experimenters, they were all undergraduate, research and doctoral students in medical universities. They had no bad habits, no infectious diseases and mental diseases, stable mood, normal physiological indexes, right hand, 20-30 years old, and an average age of 25±2. All the subjects were familiar with the equipment in advance and had no fear of resistance to the equipment. Each theme is stimulated by three different types of images, which are positive, neutral and negative images from the inter-national emotional picture library (IAPS) [9]. An instrument used in our experiment is the Canadian CTF275 full-brain magnetic mapping system. According to different regions CTF275 the distribution of all channels in the magnetoencephalogram system. CTF275 the collected data is. file at the end of the

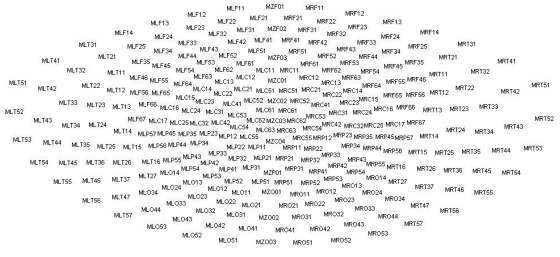

Figure 1: Channel Distribution in CTF Magnetoencephalogram System.

meg4. SPM8 is used in this experiment to extract the experimental needs in this document

When the key is pressed, the initial state is 0 s, MEG the data acquisition interval is -1s~2s, and the sampling frequency is 1200 Hz. at the same time, each set of data will get one. meg4 documents, can be processed through software SPM for our available format. There are 275 channels. There are 132 left channel ,11 middle channel ,132 right channel; The collected signals can be divided into 161 pieces of data because each set of keys is 160 times; There are 80 pictures in each group. Therefore, Data is a three - dimensional data structure, that is, the number of channels × data points × pictures, 275×161×80 dimensional data structure. But since 3D data is not easy to process in later studies, 80 emotional images of the same type there is no order of time for sampling points under stimulation, so this paper combines 80 emotional picture stimulation sampling points into a time series, that is, converting 3D data into 2D data, then the transformed data structure is 275*12880. That is, each channel is a 12880 sequence, length enough to meet our experimental requirements. Here's a diagram of the CTE275 channel(The channel distribution map of the CTF MEG system was obtained from the Magnetoencephalography Center of Nanjing Brain Hospital) and the brain structure [10]:

Channel naming rules for CTF magnetoencephalography systems are as follows:

M the first letter is the initials of the magnetoencephalogram, representing the magnetoencephalogram. E means electroencephalogram. The second letter is usually L, Z or R, to indicate the left, middle and right of the passage, that is, in which region the passage is located. The third letter refers to the area in which the F, C, P, O or T is located. The last two digits are two digits, which means coordinates, indicating which row and column the channel is in the region, of 275 channels, 1-24(MLC11-MLC63) in the left central region The following numbers are not continuous, 25-57 in the left frontal region (MLF11-MLF67 in turn), 58-76 in the left occipital region (MLO11-MLO53 in turn), 77-98 at the left apex (MLP11-MLP57 in turn), 99-132 in the left temporal region (MLT11-MLT57 in turn); 133-156 in the right central region (MRC11-MRC63 in turn), 157-189 in the right frontal region (MRF11-MRF67 in turn), 190-208 in the right occipital region (MRO11-MRO53 in turn), 209-230 at right apex (MRP11-MRP57 in turn), 231-264 in the right temporal region (MRT11-MRT57 in turn). These are the channels of symmetry. 265-268 MZC01-MZC04, respectively 269-271 MZF01-MZF03, respectively 272-274 MZO01-MZO03, respectively 275 for MZP01.

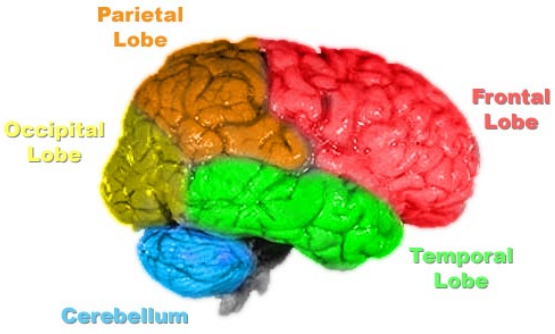

Figure 2: Structure of the Human Brain.

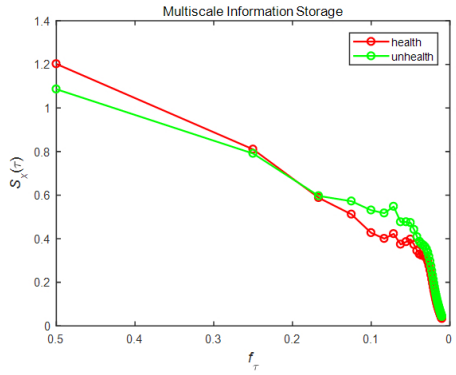

Figure 3: Results of Multi-Scale Information Storage of MEG in Healthy People and Patients with Depression under Positive Stimulation.

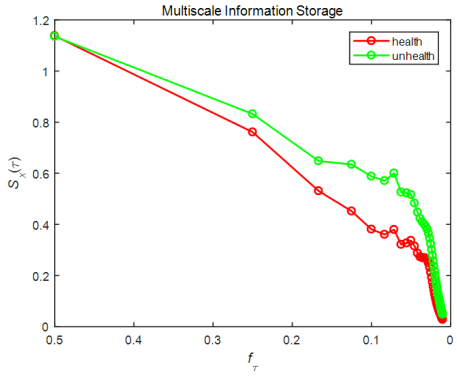

Figure 4: Multiscale Information Storage Knot of MEG in Healthy People and Patients with Depression under Negative Stimulation.

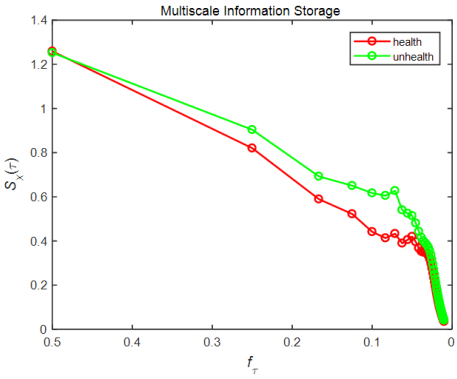

Figure 5: Results of Multi-Scale Information Storage of MEG in Healthy People and Patients with Depression under Neutral Stimulation.

Depression is an affective disease. The anterior part of the brain controls mood regulation in humans [11], so the main purpose of this experiment is to compare MEG signals in the frontal lobe. So select 25 to 57 channels belonging to the frontal region. In order to reduce the error, we also calculate the average value of it at last. The experimental results are as follows. First of all, the comparison of MEG information storage between healthy people and patients with depression under positive stimulation is shown in Figure 1, and the information storage of MEG between healthy people and patients with depression under negative stimulation is shown in Figure 2, and the information storage of MEG between healthy people and patients with depression under neutral stimulation is shown in Figure 3

From Figure 3, we can see that under positive stimulation and the time scale τ is 1, that is, when the frequency f_τ is 0.5Hz, the difference of information storage between de-pression patients and normal people is the largest. And the information storage of healthy people is higher than that of depression patients, and with the increase of time scale, the information storage of depression patients is increase of time scale.

From Figure 4, the results show that the mood of depression patients under negative stimulation is more unstable than that under positive stimulation, and there are certain fluctuations. And it can be concluded that under negative stimulation, the information storage of depression patients is higher than that of healthy people. Formula (3) shows that the entropy of current system is certain because information storage is related to conditional entropy, and entropy is the criterion of expression complexity.

From Figure 5, the results show that the magnetic map information storage of depression patients under neutral stimulation is also higher than that of healthy people, but the amplitude is higher than that of negative stimulation, because depression patients are often in a low environment and are less sensitive to negative stimuli. So the range of information storage is lower than that information storage.

4 DISCUSSION

Our analysis is carried out in the popular multi-scale entropy framework, in which the time series are firstly "coarse-grained" on the selected time scale by low-pass filtering and down-sampling. In this framework, we use the linear fractional integral autoregressive (ARFI) model to derive the analytical expression of information storage calculated on multiple time scales. Then we compare and

analyze the information storage of MEG between healthy people and patients with depression, and we find that the results can be summarized as follows:

Under positive stimulation, the information storage of healthy people is higher and lower than that of depression patients.

Under neutral or negative stimuli, with the increase of time scale, that is, the decrease of frequency, the information storage of depression patients is higher than that of healthy people.

5 CONCLUSIONS

In this study, we can conclude that under positive stimulation, we are not very good at distinguishing healthy people from depression patients. The information storage of healthy people in higher frequency range is higher than that of depression patients, while in lower frequency range, Depression patients are higher than healthy people. Under negative or neutral stimuli, whether high or low frequency range, the magnetic map information storage in depression patients is higher than that in healthy people. From formula (3), we can see that information storage and conditional entropy are related. Entropy is a criterion for evaluating complexity, and loss of complexity is considered to be a general feature of pathological dynamics. We know that the complexity of neurons in the brain is higher in healthy people than in patients with depression, which leads to higher information storage in patients with depression than in healthy people, so information storage can be used indirectly to evaluate a person's complexity, so if we want to distinguish between depressed patients and healthy people, we do a good comparison under negative or neutral stimuli. Then we can study the information storage of depression patients and healthy people in different information channels at specific time scales, the differences between different brain regions and specific channels can provide some help for clinical diagnosis of depression.

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