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Analysis of eigenvalues of oximetry change pattern based on DFA-SAMpen algorithm

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Abstract: At present, oximetry is an important indicator for monitoring patients. How to build a model to describe the model of oxygen saturation and apply it in medical practice has attracted widespread attention in the world. This article first used the DFA algorithm to detrend the original data. Then the sample entropy is calculated separately from the singular and plural scales. The mean value, variance of oximetry, regression parameters, single-scale sample permutation entropy, and multi-scale sample permutation entropy are used as the characteristic value of the typical model of oximetry. Finally, we used fuzzy clustering and Spearman's rank correlation coefficient and Kendall tau rank correlation coefficient, and then concluded that the overall oximetry content of the elderly is decreased, the stability is weak, and the regularization is not strong.

Key words: DFA algorithm; permutation entropy; fuzzy clustering; spearman correlation coefficient; oxygen saturation

Oximetry is the concentration of blood oxygen in the blood, and it is an important physiological parameter that measures human internal circulation. According to the literature, the fields of medicine and biology analyze the fluctuations of oximetry through personal physiological indicators such as BMI, cardiopulmonary function, and age. Therefore, this paper used the DFA algorithm to detrend the complex and chaotic oximetry time series, extract the sample entropy from it, to realize the characterization of biomedical signals, and to study the changes of oximetry at different ages.

1. Data sources and assumptions

The data in this article comes from the 2020 Certificate Authority Cup International Mathematical Contest Modeling B Problem, we used data from 36 individuals including age, BMI, gender, Smoking history and/or current smoking status, any significant medical conditions that could affect reading, and each subject continuously tested the oximetry for approximately 1 hour at a frequency of 1 Hz. In order to solve the problem, the following hypotheses are proposed: (1) Assume that the physical functions and health of the experimenters of all ages are the same within the standard range (18.5-23.9) of the BMI; (2) The experimental data of the subjects are all in a normal state obtained has general and biological significance; (3) Oximetry is strongly correlated with physical state.

2. Exploring the typical patterns of oximetry changes based on the DFA-PeEn algorithm

2.1 Data preprocessing

Descriptive statistics are statistics that quantitatively describe or summarize the characteristics of information

sets[1]. We Summed the time series of oximetry and calculating the maximum, minimum, average and variance of 36 samples.

2.2 The establishment of DFA algorithm

The full name of DFA algorithm is Deterministic Finite Automata. The characteristic of the algorithm is: filter out some mark points and generate a new regular sequence in the iterative process. Therefore, it is widely used in the processing of medical signals.

We took out the time series of oximetry, recorded the total length as N, and performed the summation of the sequence filter values according to the average value and standard deviation of the oximetry, which is .

Divided the summed oximetry series into n segments of equal length[2], and fitted a straight line to the time series in each fragment to indicate the trend of change in the fragment, and used this to measure the vertical characteristics of the time series after the summation scale.

Detrended the summed time series data of oximetry, took out n time periods and mark it as, and performed iterative calculation on to obtain the relationship curve between and time period n. Among them, generated by regression determines the scale index (parameter of similarity).

2.3 Calculation of permutation entropy

Permutation entropy algorithm is a method to measure the complexity of time series[3], which can effectively amplify the faint changes of time series. The permutation entropy characterizes the random degree of the time series. The smaller the value of permutation entropy is, the more regular the time series is.

1 Calculation of single-scale permutation entropy

Composed the time series into a set of m-dimensional vectors:, recorded the distance between two random vectors and as , for a certain r, counted the number of whose distance between and is less than r[5], recorded it as , and defined :. Extended the dimension to m+1, and in the same way, we could calculate the number of whose distance between and is less than r is , then the permutation entropy se is expressed as .

2 Calculation of multi-scale permutation entropy

Performed coarse-grained processing on the time series of length N[6], that is, reconstructed the phase space according to the hankel principle, and then performed s-scale analysis to obtain a coarse-grained sequence containing (N/s) elements, and calculated this coarse-grained sequence its permutation entropy.

2.4 Solution and Result

Used matlab to implement the above algorithm and get the final feature subset. Then drew the time series diagram of oximetry, and finally de-trend the chaotic oximetry signal, and drew the image of the oximetry regression fitting after processing.

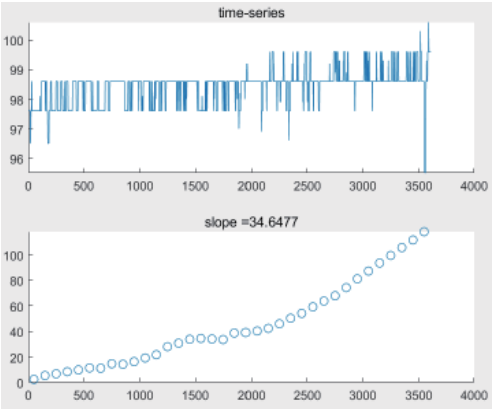

Figure 1 Examples of upward volatility

Most of the scattered point images of regression fitting show a straight upward trend. The example given in Figure 1 shows the better effect after detrending.

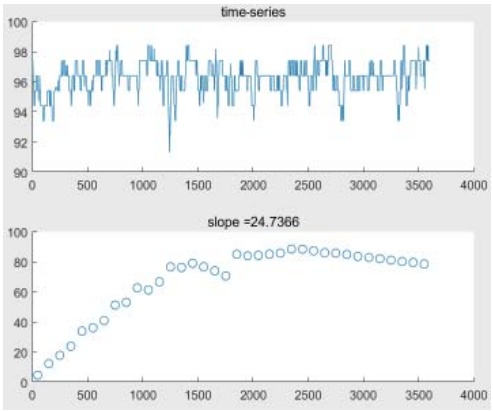

Figure2. Examples of unstable fluctuations

A very small part of the S-shaped curve contains some eventually tending to decline, as shown in Figure 2.

The DFA realization model of biomedical signals obtained five characteristic parameters to describe the typical model of oximetry, namely scale index, single-scale permutation entropy, multi-scale permutation entropy, mean value and variance.

Used the DFA algorithm to eliminate the trend fluctuation of the time series of oximetry within 1 hour, and the determination scale index generated by fitting regression to express the waveform stability of the oximetry time series change. Used the single-scale permutation entropy and the mean value mse1 of the multi-scale permutation entropy to measure the signal complexity of time series, the quantitative regularity of time series volatility and the unpredictability of nonlinear dynamic parameters are two parameters used in The regularity and complexity used to characterize the signal are produced by the new probability measurement model. The stronger the regularity is, the greater the entropy will be. On the contrary, the weaker the regularity is, the smaller the entropy will be. The basic signal pattern in the oximetry sequence is unknown, so multi-scale sample entropy can be used to better extract information. The average value represents the average level of total oximetry content. Variance represents the dispersion and change stability of the entire time series of oximetry.

3. Explore the effect of age on oximetry

We hereby set age as the only dependent variable and set up a control group. First, we quantified and preliminarily organized BMI, gender, and smoking history as the subject's score.

3.1 Model building

(1) First, normalized the subject's characteristic index matrix to obtain the normalized characteristic index matrix . Then the fuzzy similarity matrix was constructed, where was determined by the number product method. Then used the square self-synthesis method to find the transitive closure of the fuzzy similarity matrix[7], selected the appropriate confidence interval , found the -order matrix of the transitive closure , and finally classified by , the equivalent classification of the set under the level could be obtained. The optimal classification could be determined according to the size of the F statistic.

(2)Next, we calculated separately according to the two types of experimental groups classified by fuzzy clustering. We performed Spearman's rank correlation coefficient test and Kendall tau rank correlation coefficient test analysis on the characteristic values of age and oximetry[8]. Based on the calculated correlation coefficients, we studied the changes in the typical pattern characteristics of oximetry between the elderly and the young.

3.2 Solution and Result

According to the original data of the question stem, the original score matrix of 36 subjects was obtained, and fuzzy clustering was performed. The optimal classification was divided into 3 categories at the classification level of 0.75336. The results are shown in Table 1.

Table 1 Cluster result table

category	Serial number
Independent group	22
Experimental group 1	5，9，11，12，15，16，17，18，19，20，21，23，25，26，28，31，32，35
Experimental group 2	1，2，3，4，6，7，8，10，13，14，24，27，29，30，33，34，36

Let the Spearman's rank correlation coefficient be and the Kendall tau rank correlation coefficient as R. Substituted the data of the two experimental groups obtained by fuzzy clustering into the stata, the Spearman's rank correlation coefficient and Kendall tau rank correlation coefficient were obtained respectively, as shown in Tables 2 and 3.

Table 2 Correlation coefficient results of experimental group 1

correlation coefficient	Age - alpha	Age- se	Age-mse	Age-mean	Age-var
	-0.3645	-0.2264	-0.2845	-0.3247	0.1932
R	-0.2680	-0.1634	-0.2157	- 0.2353	0.1242

Table 3 Correlation coefficient results of experimental group 2

correlation coefficient	Age - alpha	Age- se	Age-mse	Age-mean	Age-var
	-0.0790	-0.0376	-0.0389	-0.2295	0.1843
R	-0.0441	-0.0294	-0.0147	-0.2353	0.1324

The 36 items of data were divided into two categories by fuzzy clustering, which excluded the effects of BMI, smoking history, and gender. According to the Spearman's rank correlation coefficient and Kendall tau rank correlation coefficient, it can be concluded that as the age increases, the regression scale index decreases, that is, the waveform stability of the time series of oximetry gradually weakens, as shown in Figure 3.

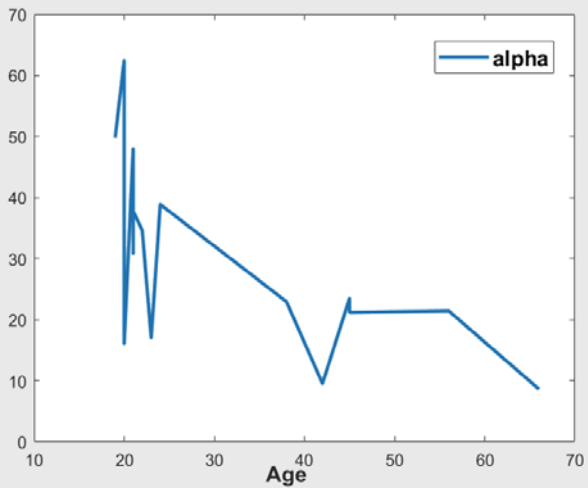

Figure 3 Wave stability of oximetry with time

As shown in Figure 4, the entropy of single-scale samples and the entropy of multi-scale samples are negatively correlated with age, indicating that the complexity of the oximetry signal in old age is reduced and the regularity is not strong.

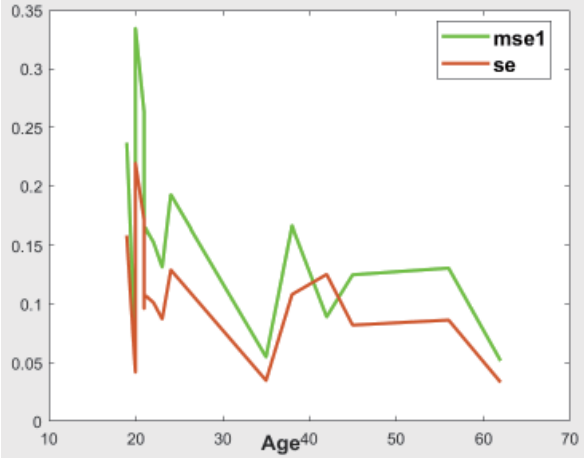

Figure 4 Permutation entropy and age distribution of single-scale samples and multi-scale samples

As shown in Figure 5, the average value is negatively correlated with age, indicating that the total oximetry of the elderly is on a downward trend, while the variance is positively correlated with age, indicating that the entire time series of the oximetry of the elderly is highly discrete.

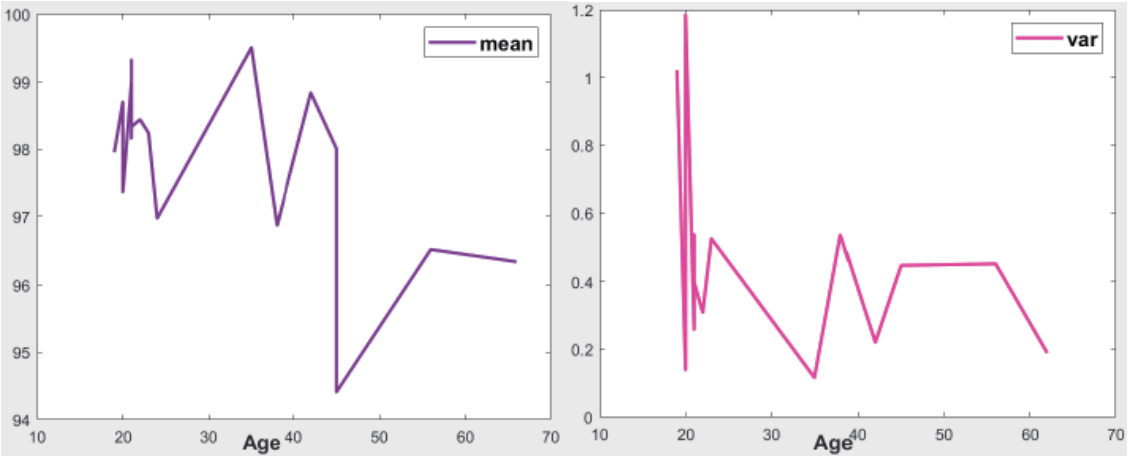

Figure 5 The mean and variance of oximetry and age distribution

4. Conclusions

(1) As an important biomedical signal, the time series of human oximetry can reflect the physical health of the human body. It is difficult to accurately study the time series of human oximetry through basic descriptive statistics such as mean and variance. Therefore, based on the mean and variance, this paper uses the DFA algorithm to detrend the time series of oximetry and eliminate chaotic time series. The trend of fluctuating oximetry and the feature information are extracted through multi-scale entropy scale and sample arrangement.

(2) Regression scale measures the stability of oximetry fluctuations, single-scale entropy and multi-scale entropy are used to measure the signal complexity and regularity of the time series. The average value represents the average level of oximetry content during this period, and the variance represents the dispersion of the entire oximetry time series[9].

(3) Based on fuzzy clustering and correlation analysis, it can be obtained that age is one of the important reasons for changes in human oximetry. As age increases, the regression scale index, sample entropy, and average value of the time series of oximetry all decrease to varying degrees, while the variance value increases. It shows that the time series of the oximetry of the elderly has weakened stability and began to produce irregular states, and the overall oximetry

content has shown a downward trend, reflecting from the side that various physical functions of the elderly have begun to decline.

References

[1] Mann, Prem S. (1995). Introductory Statistics (2nded.). Wiley. ISBN 0-471-31009- 3.

[2] Erinaldo Leite Siqueira, Tatijana Stošić, Lucian Bejan, Borko Stošić. Correlations and cross-correlations in the Brazilian agrarian commodities and stocks[J]. Physica A: Statistical Mechanics and its Applications,2010,389(14).

[3] Amandeep Cheema, Mandeep Singh. An application of phonocardiography signals for psychological stress detection using non-linear entropy based features in empirical mode decomposition domain[J]. Applied Soft Computing Journal,2019,77.

[4] Kuai Moshen, Cheng Gang, Pang Yusong, Li Yong. Research of Planetary Gear Fault Diagnosis Based on Permutation Entropy of CEEMDAN and ANFIS.[J]. Sensors (Basel, Switzerland),2018,18(3).

[5] Ai Tinghua, He Yakun, Du Xin. Changes of information entropy in GIS data scale transformation [J]. Geography and Geo-Information Science.2015.31(02):7-11.

[6] Wu Zhe, Zhang Qiang, Huang Huameng, Cheng Fangfeng. Research on Fault Diagnosis of Composite Planetary Gear Based on Multi-Scale Permutation Entropy [J]. Machinery Design & Manufacture,2020(09):182-186.

[7] An Gang Zhang, Zi Fei Fan, Heng Song. Evaluation Model of Profile Control Layers' Selection Based on Fuzzy Cluster Analysis[J]. Advanced Materials Research,2013,2482.

[8] Zhang R Q. Analysis of autonomic nerve patterns in patients with hypertension based on short-term heart rate variability [D]. Southwest University,2020.

[9] Boubacar Ibrahim, Harouna Karambiri, Jan Polcher, Hamma Yacouba, Pierre Ribstein. Changes in rainfall regime over Burkina Faso under the climate change conditions simulated by 5 regional climate models[J]. Climate Dynamics,2014,42(5-6).