Chapter 5
Comprehensive Feature Index for Meridian Information Based on Principal Component Projection

Jianhua Qin and Chongxiu Yu

Abstract Specifically for quantify and extract meridian information, a comprehensive multi-acupoint feature index was given. The feature parameters of single acupoint were extracted and reconstructed based on AR parameter model. Then feature weight was obtained by objective weighting method and feature matrix was weighted. The ideal feature vector was built based on orthogonal transformation of eigenvalues in meridian feature space. Based on PCP, the distance between each feature vector and the ideal model vector was calculated, and the projection value of fixed-weighted feature matrix on ideal feature vector was obtained. The simulation results show that the method can be more stability and higher around 3 % in the recognition rate than the main acupoint in human multi-acupoint system. The same results also show that the recognition rates can be coincided with sort results.

Keywords Human Meridian · PCP · Orthogonal transformation · Feature extraction

5.1 Introduction

Life activities of the human body are an extremely complex process, and somatic information are transferred and communicated through meridian systems. "Biological Cybernetics" studies show that, the so-called "gas, blood" in the medicine meridian theory means "information carrier", "channels, collaterals" corresponds to "information channel", and "acupoints" corresponds "information input or output". The majority experts and scholars at present study the relationship between meridian and human physiology changes based on single acupoint [1].

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The studies show that acupoint has some unique signal features such as high complexity, uncertainty, multi-level and multi-development. However, the studies also show that some acupoints are closely related to body functions, and others are very low or even irrelevant to physiological functions. Furthermore, the acupoints are affected by the internal rules, the external stimuli, and other factors. So the single acupoint features are not very good at reflecting the whole meridian.

Statistics believe that everything has its particularity, contingency, and randomness, but not chaotic, not rules. Learn from extraction idea for multi-lead EEG feature [2, 3], and cluster and discriminant analysis [4, 5], this paper constructs a new comprehensive multi-acupoints feature index for channels and collaterals that identifies the physiological changes of the human body based on the principal component projection method (PCP).

5.2 Extraction and Reconstruction to Single Acupoint

According to the traditional Chinese medicine theory, each channel and collateral line has a certain number of acupoints which are the response points of human organ and physiological state and play a important role to adjust channels-and-collaterals and viscera-and-blood. Therefore, the acupoint feature parameters are established.

The time sequence parameters model method is a mature method in physiological signals of meridian and acupoint, and especially the AR parameter model is commonly used to extract the feature parameters of acupoint [6, 7]. The formula of the AR parameter model is given by:

$$s(n) = -\sum_{m=1}^{p} a_m s(n-m) + u(n) + w(n) \tag{5.1}$$

where $u(n)$, $s(n)$, $w(n)$ denote the input excitation signal, the output impedance signal, and the white noise sequence. Here, p is the model order, and a_m is the AR model parameter with the order for p.

Order p is a key problem to accurately reflect somatic state. When order number is very low, the AR spectrum is too smooth to reflect the spectrum peak. And when order number is very large, the AR spectrum is instability and easily produce false peak. In this paper, the AR model order is obtained by AIC criterion, and optimal order estimation is 39 based on a large number of meridian impedance samples.

The AR model parameters in formula (1) are directly used as the signal feature in the traditional feature extraction method. But the number of model parameters are very large, and at the same time each parameter only express the partial information of the system, which inevitably leads to reduce the classification capacity. So the model parameters are not very suitable for channels and collaterals diagnostic, and need to be reconstructed. The reconstructed feature is obtained by AR spectrum. Figure 5.1 shows the AR spectrum for three acupoint impedance samples.

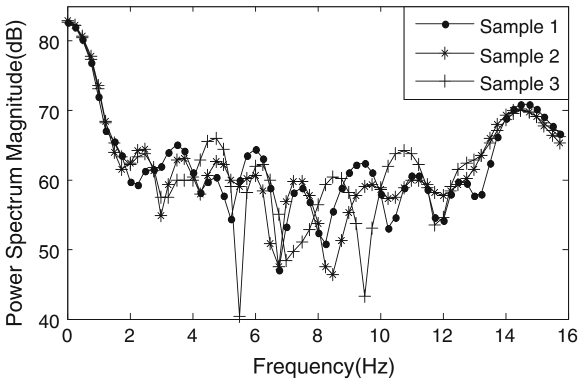

Fig. 5.1 AR spectrum for three meridian impedance samples of a tester

As can be seen from Fig. 5.1, AR model spectrum line is relatively smooth with multiple peaks in the frequency domain. The peaks are prominent and accurate with overcoming spectrum lines leak, emergence of side-lobe, low-resolution, and submerged by weak signal. It shows that AR model spectrum is conducive to the automatic computer extraction of feature parameters. And under the frequency less than 2 Hz, the spectrum line also decreases monotonically and is not well in reflecting acupoint differences. So amplitude maximum peak between 2–16 Hz is selected as feature peaks, and the frequency and the amplitude of the center cite in 2–16 Hz are extracted and named as center frequency and center peak. The energy of the frequency part, in which the frequency is higher than the frequency in the feature peaks, is named for high frequency energy, and then the high frequency energy is represented as high frequency percentage in the total frequency energy. Thus the feature vectors of acupoint impedance signal are composed of the five AR spectral features. Experimental results show that the feature vector can be very well in reflecting the signal features, and reduce the calculation and classification for the next step.

5.3 Comprehensive Feature Extraction for Channels

Firstly, the number of the feature-extracted acupoints in human channel line is set to m, and each acupoint has been described to the AR spectral feature vector ($\vec{a}' = \{a'_1, a'_2, \cdots, a'_n\}$). Thus sample matrix for the channels features may be written as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} = (x_{ij})_{m \times n} \tag{5.2}$$

where i, j are the vector number and the acupoints number. Here, the eigenvector of the i-th acupoint corresponds to the i-th row of X (x_{i1}, $x_{i2} \cdots x_{in}$), and the j-th column acupoint feature corresponds to the j-th column of X (x_{1j}, $x_{2j} \cdots x_{mj}$). The j-th column acupoint feature means the evaluation index value of the j-th feature acupoints.

In the sample matrix composed of the multi-acupoints and multi-features, feature types are very big difference, and thus the features are standardized. Based on the linear function, the formula (2) is normalized and transformed to the new feature sample matrix, which is expressed as:

$$y_{ij} = \begin{cases} \dfrac{x_{ij} - \min\limits_{1 \le i \le m}(x_{ij})}{\max\limits_{1 \le i \le m}(x_{ij}) - \min\limits_{1 \le i \le m}(x_{ij})} \\ \dfrac{\max\limits_{1 \le i \le m}(x_{ij}) - x_{ij}}{\max\limits_{1 \le i \le m}(x_{ij}) - \min\limits_{1 \le i \le m}(x_{ij})} \end{cases}$$

where y_{ij} meet to $y_{ij} \in (0,1)$.

When the proportion of the single-acupoint features in multi-acupoints comprehensive features is larger, the single-acupoint features contain more information, and are stronger to be identified. So feature weight is introduced to denote the attention degree of the single acupoint features in the multi-acupoints. In the channels and multiple acupoints system, feature weight (λ_{ij}) of the single-acupoint (x_{ij}) is:

$$\lambda_{ij} = x_{ij} / \sum_{i=1}^{m} x_{ij} \tag{5.3}$$

The discrepancy between each acupoint is directly reflected by the difference degree of information entropy in the meridian system. In order to facilitate comparison and analysis, the information entropies for each acupoint are normalized and the result is:

$$H_j = -\left(\sum_{i=1}^{m} \lambda_{ij} \,\mathrm{In}\, \lambda_{ij} \right) / \mathrm{In}\, m \tag{5.4}$$

Then, feature weights of the j-th features are obtained based on objective weighting method and expressed as:

$$w_j = (1 - H_j) / \sum_{j=1}^{m} (1 - H_j) \tag{5.5}$$

Features matrix Y is weighted by using the feature weights (w_j). Let $z_{ij} = w_{ij} y_{ij}$. Where $\mathrm{Z} = (z_{ij})_{n \times \mathrm{m}}$ is weighted feature matrix and the feature vector for acupoints is:

$$\vec{d}_i = (z_{i1}, z_{i2}, \cdots, z_{im}), (i = 1, 2, \cdots, n) \tag{5.6}$$

The correlation between acupoints in the meridian system often causes mutual interference and overlapping to feature information, and thus the relative position of feature vector is difficult to analyze objectively. This may be solved by the orthogonal transform method that can filter duplicate information of the acupoints.

Set up: Feature values of weighted feature matrix are expressed as $\lambda_1, \lambda_2, \ldots, \lambda_m$ (It satisfies the inequality: $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m$), and correspond to the flat feature vector for $\alpha_1, \alpha_2, \ldots, \alpha_m$. Let $\mathrm{A} = \{\alpha_1, \alpha_2, \ldots, \alpha_m\}$ and the weighted feature matrix are orthogonal transformed by Z. Thus the modified weighted feature matrix is obtained by equation $\mathrm{U} = \mathrm{ZA} = (u)_{m \times n}$, and denoted as:

$$\vec{d}_i' = (u_{i1}, u_{i2}, \cdots, u_{in}), (i = 1, 2, \cdots, m) \tag{5.7}$$

where $\vec{d}_i'$ is the influence value of the i-th acupoint in the meridian syndrome.

Here, if the influence value is higher, the influence of acupoint is stronger. Conversely, if the influence value is smaller, the influence of acupoint is weak.

First of all, take the optimal features as reference features, and maximum feature parameters in the channels system are used to construct the optimal feature vector. The feature vector is named to the ideal acupoint feature vector, and expressed as

$$\vec{Z} = (\vec{z}_1, \vec{z}_2, \cdots, \vec{z}_n)' \tag{5.8}$$

The expression (8) is united and then the following equation is obtained.

$$\vec{Z}_d = \frac{1}{\left|\vec{Z}\right|}\vec{Z} = \frac{1}{\sqrt{\vec{z}_1^{\,2} + \vec{z}_2^{\,2} + \cdots + \vec{z}_n^{\,2}}}\vec{Z} \tag{5.9}$$

Secondly, the projection value of modified weighted feature matrix in the reference feature vector is obtained by the PCP method and expressed as:

$$D_i = \vec{d}_i'\vec{Z}_d = \frac{1}{\sqrt{\vec{z}_1^{\,2} + \vec{z}_2^{\,2} + \cdots + \vec{z}_n^{\,2}}}\sum_{j=1}^{n}\vec{Z}_j u_{ij} \tag{5.10}$$

where D_i is the projection value set that is the channels comprehensive features.

5.4 Experimental Simulation and Analysis

In the experiment, the experimental objects are 25 normal volunteers with 25–35 years age and under the before and after strenuous exercise state. The measurement for each volunteer is repeated by 50 times in each state. In the experiment, the stimulation point and the reference electrode point are placed in Daling acupoint of Jueyin Pericardium Channel and Tianquan acupoint. And the received electrodes are placed in Shaoshang, Yuji, Taiyuan, Jingqu, Lieque,

Table 5.1 Features sample of Taiyin Lung channel of hand before and after standardization under normal human condition

Acupiont	Feature parameter before standardization					Feature parameter after standardization				
	Spectral peak	Center frequency	Center peak	Total frequency energy	High frequency energy	Spectral peak	Center frequency	Center peak	Total frequency energy	High frequency energy
Shaoshang	59.4818	5.4375	52.6634	363.8079	0.7113	0.5229	1.0000	0.1421	0.1333	0.3240
Yuji	61.1296	5.3594	58.9543	373.5321	0.7700	0.8968	0.6480	0.890	0.3433	0.5377
Taiyuan	61.5845	5.2969	59.8814	403.9406	0.6384	1.0000	0.3664	1.0000	1.0000	0.0586
Jingqu	60.1877	5.2156	54.9233	369.0267	0.7607	0.6831	0.0000	0.4107	0.246	0.5038
Lieque	58.6158	5.3000	55.3983	361.2367	0.8970	0.3264	0.3806	0.4671	0.0778	1.0000
Kongzui	57.7861	5.2163	51.4682	361.0062	0.7059	0.1381	0.0032	0.0000	0.0728	0.3043
Chize	58.0686	5.2844	53.5268	357.6359	0.7180	0.2022	0.3100	0.2447	0.0000	0.3484
Xiabai	59.2371	5.3172	54.6212	362.123	0.6223	0.4674	0.4579	0.3748	0.0970	0.0000
Tianfu	60.8983	5.4063	55.6170	387.6739	0.7850	0.8443	0.8594	0.4931	0.6487	0.5923
Yunmen	57.1773	5.4267	55.2457	364.4686	0.8317	0.0000	0.9510	0.4490	0.1476	0.7623
Zhongfu	59.4088	5.4375	53.8136	360.1794	0.7695	0.5063	1.0000	0.2788	0.0550	0.5359

Table 5.2 Comprehensive information feature of Taiyin Lung channel of hand for 6 testers before and after exercise

State	Tester	Shaoshang	Yuji	Taiyuan	Jingqu	Lieque	Kongzui	Chize	Xiabai	Tianfu	Yunmen	Zhongfu
Before strenuous exercise	1	0.2328	0.3980	0.0826	0.3634	0.7037	0.2131	0.2463	0.0102	0.4368	0.5398	0.3800
	2	0.2287	0.4012	0.0876	0.3872	0.7015	0.2212	0.2378	0.0200	0.3998	0.5421	0.3978
	3	0.2382	0.3887	0.0872	0.3321	0.6993	0.2229	0.2147	0.0172	0.4207	0.5212	0.4123
	4	0.2169	0.4109	0.0852	0.3492	0.7102	0.2082	0.2064	0.0178	0.4380	0.5683	0.4001
	5	0.2465	0.4321	0.7911	0.3725	0.7077	0.2180	0.2300	0.0203	0.4365	0.5676	0.3965
	6	0.2301	0.3771	0.8198	0.3612	0.6890	0.2008	0.2289	0.0117	0.4074	0.5307	0.3910
After strenuous exercise	1	0.1367	0.0709	0.5783	0.1344	0.2578	0.4573	0.4507	0.6624	0.1032	0.2280	0.1324
	2	0.1207	0.0723	0.6523	0.1723	0.2000	0.4726	0.4821	0.5842	0.1313	0.1001	0.1238
	3	0.1233	0.1201	0.6876	0.1721	0.2372	0.4321	0.3902	0.7432	0.2283	0.2342	0.1231
	4	0.1326	0.1231	0.6232	0.1800	0.2438	0.4721	0.4793	0.5832	0.0991	0.2543	0.1782
	5	0.1351	0.1483	0.6327	0.1743	0.2265	0.4962	0.4392	0.6666	0.1413	0.1867	0.1896
	6	0.1372	0.1821	0.6789	0.1657	0.2012	0.4583	0.4203	0.7029	0.1772	0.1938	0.1628

Kongzui, Chize, Xiabai, Tianfu, Yunmen and Zhongfu acupoint of Taiyin Lung Channel of Hand. The excitation signal in the experiment is the multisine (it is the periodic current signal superimposed by multiple positive (I) sine wave), in which sampling frequency for the excitation signal is 1 kHz, and the received signal is voltage signal [8]. The part result was given by Tables 5.1 and 5.2. (Due to limited space, only the results of six testers were listed).

In order to analyze the multi-acupoints feature index, the Elman Neural Network method is used to recognize the comprehensive feature vector of multi-acupoints and the feature vector of Shaoshang, Chize and Tianfu acupoint. In the simulation experiment, status output is set up for 0 with the before-exercise state and for 1 with the after-exercise state, and permissible error of status output is 0.2. It means that the output result in 1 ± 0.2 is considered to be the moving state. In addition, the first 10 sets of data in each target are as learning samples and the last 40 sets are testing samples. The recognition results are shown in Figs. 5.2, 5.3. In Figs. 5.2, 5.3, the ordinate and the abscissa are the recognition rate and the test personnel number.

As can be seen from Figs. 5.2 and 5.3, the average recognition rate of the multi-acupoints feature that is above 95 % under the before-exercise state and above 94 % under the after-exercise state, is about 3 % higher and more stable than the single acupoint in the same state. It can also be seen from Figs. 5.2 and 5.3, the recognition rate in Tianfu acupoint is higher than Shaoshang acupoint and Chize

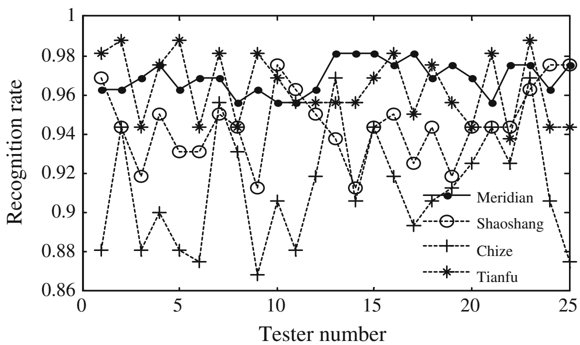

Fig. 5.2 Recognition results based on neural network before exercise

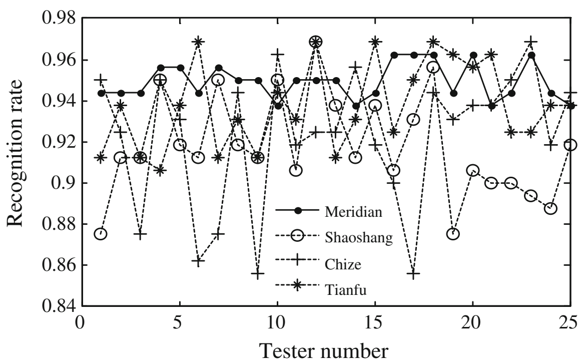

Fig. 5.3 Recognition results based on neural network after exercise

acupoint. It indicates that the feature weight of Tianfu acupoint in the channel (Taiyin Lung Channel of Hand) system is higher than other two acupoint, which is coincide with the PCP sort of the whole channel. The same result is also proven in other channel.

5.5 Conclusion

Inspired by cluster and discriminant analysis, a comprehensive multi-acupoint feature index method is established based on PCP method in this paper. Feature weight and orthogonal transformation are introduced to this method, and then principal component analysis method and projection method are merged organically to solve acupoint difference-degree in channels and collaterals system, mutual interference and overlapping of information feature and unit schedule for acupoints feature in a different time or space. The recognition results based on Elman Neural Network show that the recognition rate of this method is more stable and about 3 % higher than the single acupoint. And at the same time, the recognition rate of single acupoint coincides with the PCP sort. It sets up the foundation for further identification of human disease states based on the meridian signal.

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