Melancholia Diagnosis Based on GDS Evaluation and Meridian Energy Measurement Using CMAC Neural Network Approach

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Abstract: In this paper, a preliminary result about the melancholia diagnosis scheme based on the analyses of depression questionnaire and the meridian energy of human body using CMAC (Cerebellar Model Articulation Controller) neural network approach is proposed. Firstly, a large amount data obtained from hospital, recorded the aged patients' depression rating scales and the 12 sets meridian energy signals, are sieved out three disease groups' patterns. Assuming the recorded data can describe the necessary features of the melancholia patient. Then, we built a CMAC neural network to learn the melancholia features depending on the three disease groups' patterns. By the sufficient training, the diagnosis architecture will memorize the features of the selected melancholia patient patterns. Finally, the built diagnosis system can used to diagnose the depression scale by inputting the 12 sets meridian energy signals of human body into CMAC neural network. To benefit the pattern collection, re-training, diagnosis and the data analyses, a PC-based friendship operation interface is developed in this paper also. Such as the function of new pattern addition, retraining, and the memory weights distribution plots are appeared in the interface.

Key-Words: energy medicine, disease diagnosis, melancholia, depression questionnaire, CMAC, GDS, neural network

1. Introduction

As the progress of science and technology, there are many new diseases appear in the world, such as cancer, AIDS, melancholia and so on. However, it is still lack of well known methods to treat these serious diseases. Usually, early diagnosis and prophylaxis become the major index of prognosis. Therefore, to develop novel diagnosis scheme for these century diseases becomes an important topic.

For example, melancholia is a subtype of depression, which is usually diagnosed by the presence of a set of subjective symptoms, such as diurnal variation in mood, sleep disturbance and change in appetite, in addition to symptom of low mood. Generally, people don't know suffered from melancholia and miss the diagnosis in early stage until tragedy happened. Unfortunately, melancholia diagnosis is not an easy task. Because it is hard made impression of melancholia by general objective examination, such as blood test, X-ray, CT scan, and ultra-sonography. The diagnosis of melancholia usually focused upon the development of a clinician-rated behaviorally measurement. Sometimes, the patient needs to fill in depression questionnaire, such as shown in Table 3 and then the doctor evaluate the possibility of melancholia. However, it is not a good objective diagnosis methodology. The diagnostic correctness strongly depends on if the patient fill in the measure table properly and honestly. Therefore, how to develop a new objective diagnosis scheme is the major purpose of this paper.

Energy medicine is a new science and technology. Measuring and analyzing the 12 sets meridians energy of human body is one kind of detective methods in energy medicine. The 12 sets meridians include lung, pericardium, heart, small intestine, sanjao, large intestine, spleen, liver, kidney, bladder, gallbladder and stomach meridian. Through a long time research, the standard test points are shown in Figure 1[1]. According to energy medicine and traditional Chinese medicine theories, most of the health conditions can be discovered by the 12 sets meridian energy signals. In this paper, we analyse a large amount data, recorded the aged patients' depression questionnaire and the 12 sets meridian energy signals, and sieved out three groups' patterns. Then we built a CMAC neural network to learn the features of meridian energy for melancholia.

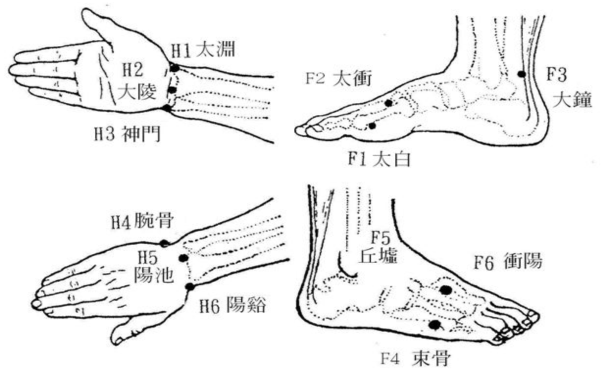

Fig.1 Detection points of meridian energy

When finished the training, the CMAC diagnosis architecture can be utilized to diagnosis the melancholia by measuring the 12 sets meridian energy signals. It is different from traditional energy diagnosis schemes strongly depend on the clinician-rated behaviorally measurement.

2. Brief description of CMAC neural network

In 1975, Albus proposed the CMAC neural network and applied it to the robotic manipulator control [2]. Figure 2 schematically depicts the CMAC networks [3], which like the models of the human memory to perform a reflexive processing. The CMAC, in a table look-up fashion, produced a vector output in response to a state vector input. The mapping processes include the quantization, binary similar memory addresses; restated, if the input states coding, excited addresses coding and summation of the excited memory weights [4-6]. The characteristic of the mapping processes is that similar inputs excite are close in input space, then their corresponding sets of association memory cells overlap. For example, x_1 and x_2 are similar (close), if x_1 excites the memory addresses a_1,a_2,a_3,a_4 , then x_2 should excites the memory addresses a_2,a_3,a_4,a_5 or a_3,a_4,a_5,a_6 depending on their similarity. The inputs are said to be highly similar if two inputs excite the same memory addresses. Inputs with lower similarity would excite fewer same memory addresses.

Therefore, we can utilize the known training patterns to train the CMAC neural network. The CMAC will store the specific signal feature on the

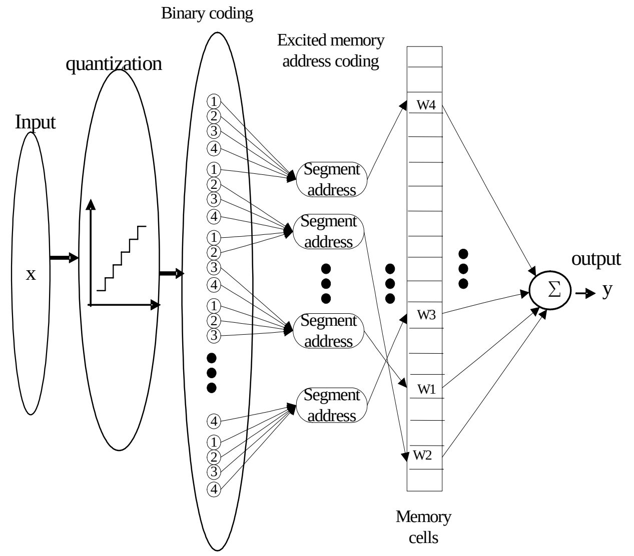

Fig.2 Functional schematic of CMAC neural network

excited memory addresses separately.

When the input signal is same as the training data, it will excite the same memory addresses and output exactly signal type. Non-training data input the CMAC will excite different memory addresses depending on the similarity degree with the training patterns. Assuming the output is trained to equal one to denote a specific signal type, that is the node output one(1) confirms what signal type is. Then inputting the diagnosed data to the CMAC system, the node output can express the possibility of the specific signal type. In this paper, the meridian energy signals for melancholia patients are the training patterns of the proposed CMAC diagnosis system.

3. CMAC based melancholia diagnosis system

3.1 pattern collection

In this research, all the data obtained from Taichung Hospital (in Taiwan). The participated aged people accepted the depression questionnaire filling and the MEAD (Meridian Energy Analysis Device [1]) energy medical examination simultaneously. Usually, depression questionnaire for aged people is shown as Table 3 and we call it geriatric depression scale which is a self-report scale designed to be simple to administer and not to require the skills of a trained interviewer [7]. As shown in Table 3, each of the 30 questions has a yes/no answer, with the scoring dependent on the answer given. To add the matching answer (one point) as shown in Table 3 will obtain the GDS value. Generally, if GDS value is more than 20, patient with severe melancholia will be highly suspected. In this paper, we sieved out three groups' patterns and labeled as L_1, L_2 and L_3. L_1 denotes high possibility with melancholia (severe) and the GDS value larger than 17. L_2 expresses low possibility with melancholia (mild), GDS value between 10 to 16. L_3, GDS value smaller than 10, represents people with melancholia is less likely (normal).

MEAD device, based on the Ryodoraku theory which thought the abnormality or disease of viscus could be reflected in the change of biological electric current, provides precise professional medical check-up. Generally, the operator used MEAD to measure the meridians' energy by using a special probe to touch the measuring points as shown in Fig. 1 orderly [1]. Figure 3 shows the example for the probe touches the H1 point of left hand. In the test processes, the MEAD software also shows the test point orderly, such as Fig. 4. Assuming the operator runs the measurement processes properly, the 12 sets meridian energy would be recorded and displayed in bar diagram as Fig. 5.

Fig.3 Photo for meridian energy measurement.

Fig.4 Photo for Mead displays the test point

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Noted each sets meridians contain left side and right side. In Fig. 5, the leftest two bars denote the lung meridian energy of left side and right side. Generally, we quantized the meridian energy as five levels and encoded as -2 to 2 to denote pathologic deficiency reaction, physiological deficiency reaction, normal reaction, physiological excited reaction and pathologic excited reaction respectively.

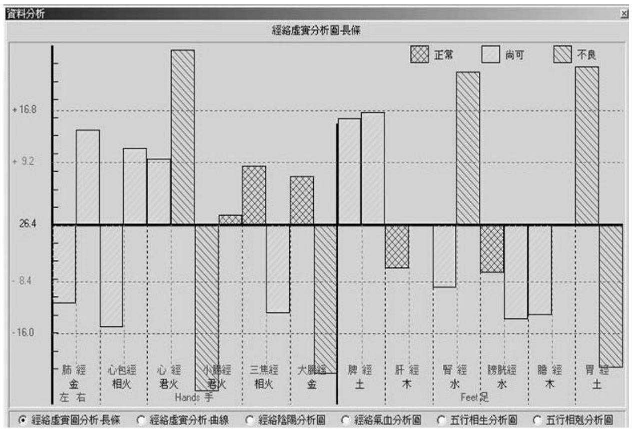

Fig.5 Bar diagram of 12 sets meridian energy signals

The physiological reaction graph and quantized value are shown in Fig. 6.In this paper, we just used the total energy to represent the energy of each meridian. For each meridian, the total energy is the sum of the quantized absolute value of left side energy and right side energy. Therefore, the partial sieved out patterns are rearranged as Table 1. In Table 1, T_i represents the quantized total meridian energy of the i-th meridian.

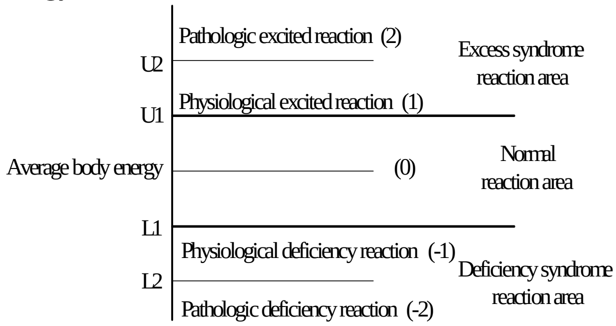

Fig.6 Physiological reaction graph and quantized value

3.2 CMAC melancholia diagnosis system

Based on the patterns collection, three melancholia patient levels (severe, mild, normal) and 12 meridians energy inputs, we built the diagnostic architecture as Figure 6. It includes an input layer with 12 inputs, quantization operation, excited memory addresses coding unit, three parallel memory layers and three output nodes. The operations of the proposed scheme contain a training mode and a diagnosis mode. Details are illustrated as follows.

3.2.1 Training mode

In training mode, the patterns of melancholia degree types L_i (i=1,2,3) are used to train the memory layer i which memorizes the feature of melancholia degree L_i only. Inputting the L_i patterns to the diagnosis system, via a series of mappings, including quantization, binary coding,

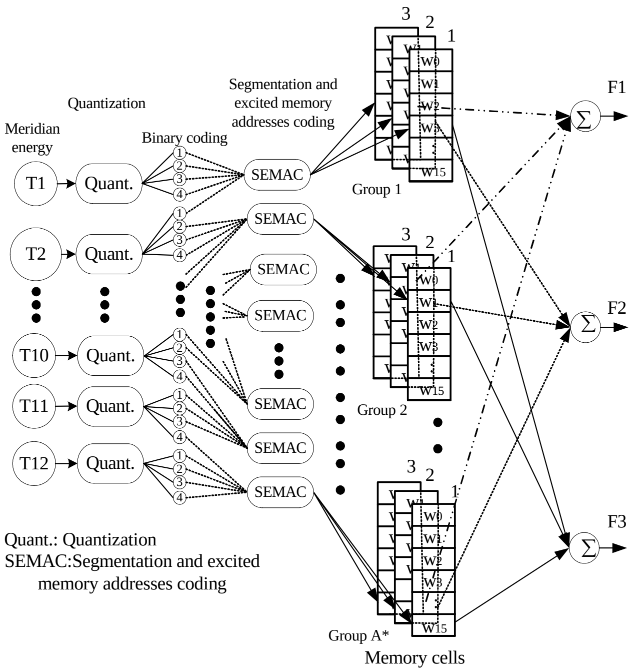

Fig.7 Melancholia diagnosis system using CMAC NN and meridian energy information

segmentation, excited memory addresses coding and summation of the excited memory addresses weights,the CMAC will produce an output value. Assuming the output value is trained equal to one to denote a specific melancholia degree, i.e. the node output one confirms what melancholia degree is. Then inputting the diagnosed data to the diagnosis system, the node output can express the possibility of the specific melancholia degree. In Table 1, bold type rows are test data, they did not input to the built diagnosis system in training mode.

3.2.2 Quantization

As shown in Figure 7, the input signals are first put through the quantization mapping to produce a quantization level output. If all the T_i signals are expressed as integral, this step can be omitted. Otherwise, the quantization output can be calculated as follows [8]

$$q_i = Q(T_i, T_{i\min}, T_{i\max}, q_{i\max}), \quad i = 1, \cdots, k \qquad (1)$$

where k is the number of input pattern for specific melancholia degree patient. The resolution of this quantization depends on the expected maximum and minimum inputs, $T_{i\max}$ and $T_{i\min}$, and on the number of quantization levels, $q_{i\max}$. To simplify the quantization process, here we consider the $q_{i\max}$ as 15. That is for each input signal will be quantized as 0 to 15. As shown in the quantization mapping diagram of Figure 8, the quantization level of each input signal can be calculated as

$$q_{Ti}(T_i) = ceil((T_i - T_{i\min})/[(T_{i\max} - T_{i\min})/(q_{i\max} - 1)] \qquad (2)$$

where ceil(x), the instruction of Matlab, rounds the elements of x to the nearest integers towards infinity. For example, in the first row of Table 5, the quantization level of each input signal is calculated as0111,0000,0000,1110,0111,1011,0000,0111,1110,0000,1110,0110.

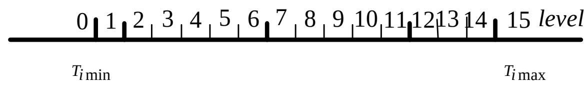

Fig.8 Quantization mapping diagram

3.2.3 Binary coding

As described above, concatenating the 12 quantization levels, we have the following binary string.

011100000000111001111011000001111110000011100110B

The characteristic of CMAC NN is that similar inputs excite similar memory addresses. The coding of excited memory addresses must satisfy such condition. Using the binary string will benefit the excited memory addresses coding described below and reduce the memory space. It is different from the traditional coding scheme described in [3].

3.2.4 Segmentation, excited addresses coding and output mapping

For example, take five bits of the last 48 bits string as a segment (group) and rewrite as follows.
0111000000001110011110110000011111100000111
00110

Then from LSB (least significant bit) to MSB (most significant bit) the excited memory addresses are coded as a1＝00110b＝6、a2＝00111b＝7、a3＝11000b＝24、a4＝01111b＝15、a5＝10000b＝16、a6＝11101b＝29、a7＝11001b＝25、a8＝00001b＝1、a9＝10000b＝16、a10＝011b=3. It implies that the excited memory addresses number, A^*, is ten. The feature of the specific melancholia degree type will distributed store on the ten excited memory addresses. To add the weights of excited memory addresses will produce the CMAC output. The output of CMAC can be expressed as

$$y = \sum_{i=1}^{A*} w_i^{ai} \ ,i=1,\cdots,A^* \qquad (3)$$

where w_i^{ai} denotes the ai-th addresses of group i.

3.2.5 Learning rule

Assuming the memory layer i (i=1,2,3) output one denotes the melancholia degree L_i is confirmed, then one can be thought as the teacher and the supervised learning algorithm can be described as [3,4]

$$w_{i\,(new)}^{ai} \leftarrow w_{i\,(old)}^{ai} + \beta \frac{Y_d - Y}{A*} \ , \quad i = 1,2,...,A^* \qquad (4)$$

where $w_{i(new)}^{a_i}$ are the new weight values after the weights tuning, $w_{i(old)}^{a_i}$ are the old weight values before weight tuning, and *ai* denotes the excited memory addresses, β the learning gain($0<\beta<1$), $y_d=1$ the desired output, Y the real output.

3.2.6 Learning convergence and performance evaluation

From [9], the convergence of a supervised learning algorithm can be guaranteed. Assuming the i-th (i=1,2,3) layer output one denotes the system has melancholia degree L_i, and the number of training patterns is N_p. y_i is the CMAC output for pattern i. Let the performance index be

$$E=\sum_{i=1}^{N_p}(y_i-1)^2 \tag{5}$$

when $E<\varepsilon$ the training process will stop. (ε is a small positive constant).

3.3 Diagnosis mode

When the training mode is finished, the CMAC diagnosis system can be used to diagnose melancholia degree. Inputting the diagnosis data (quantized total meridian energy) to the diagnosis system, the operations of CMAC NN are same as the training mode. But in diagnosis mode, the same excited memory addresses weights of every memory layer are summed up and each layer has one output value. If the input signal is the same as the training patterns of L_i, it will excite the same memory addresses of layer i and layer $i's$ output near one denotes the melancholia degree type is L_i. But other layer' s output, generally, far away from one expresses a low possibility of melancholia degree L_j ($j\neq i$).Other features of the proposed scheme are described as follows.

3.4 Diagnosis algorithm

Based on the configuration of Figure 7 and described above, the diagnostic flowchart is shown in Figure 9 and the diagnosis algorithms are summarized as follows.

3.4.1 Training mode

step 1 Build the configuration of CMAC melancholia diagnosis system. It includes 12 input meridian signals, 3 parallel memory layers and 3 output nodes.

step 2 Input the training patterns, through quantization, segmentation, excited memory addresses coding, and summation of excited memory addresses weights to produce the node output.

step 3 Calculate the difference of actual output and the desired output (y_d=1) and using equation (4) to update the weight values.

step 4 Train performance evaluation. If $E<\varepsilon$, the training is finished. Save the memory weights. Otherwise, go to step 2.

3.4.2 Diagnosis mode

step 5 Load the up to date memory weights from the saved file.

step 6 Input the diagnosed data.

step 7 Quantization, segmentation, excited memory address coding, and summation of the excited memory weights using equation (3).

step 8 Output the diagnosis result.

step 9 Is the next data to be diagnosed? Yes, go to step 6. Otherwise, stop the diagnosis operation.

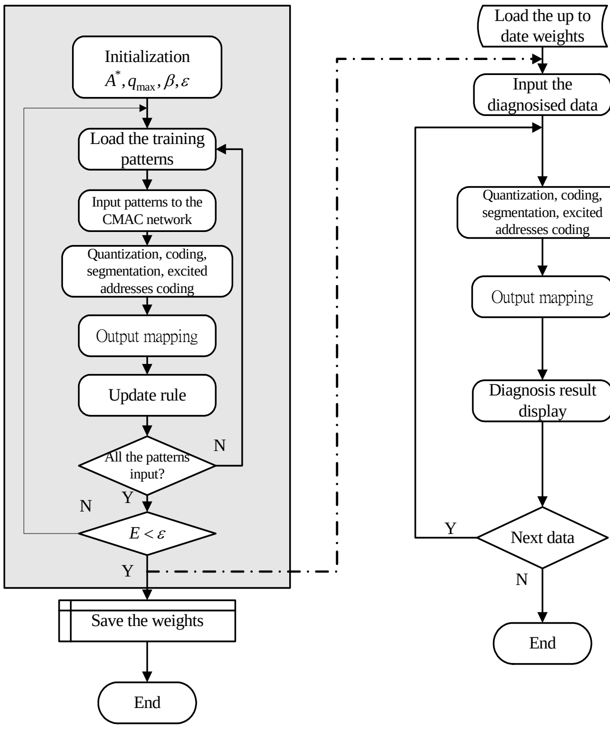

Fig. 9 Flowchart of CMAC melancholia diagnosis system

In Figure 9, the left hand side represents the off-line training mode flowchart and right hand side is the on-line diagnosis mode. The dashed line from left to right denotes the system first time to be started.

4. Case study and discussion

To demonstrate the effectiveness of the proposed scheme, we sieved out 7 sets data for each melancholia degree to test the possibility. Five sets are utilized as training patterns and the others are test data. All data are list in Table 1 and the bold type rows represent the test data.

Using the training patterns of Table 1 to train the CMAC diagnosis system, take q_{max} 16, coding bit 5, and training times 10, the weights distribution plots of memory layers 1 to 3 for group 1 to 10 are shown in Figure 10 after training. Increase the training pattern, the CMAC NN will record all the features on the memory and the weights distribution plot will somewhat like the brain waves.

Inputting the training patterns and test data to the CMAC diagnosis system again, the diagnosis results

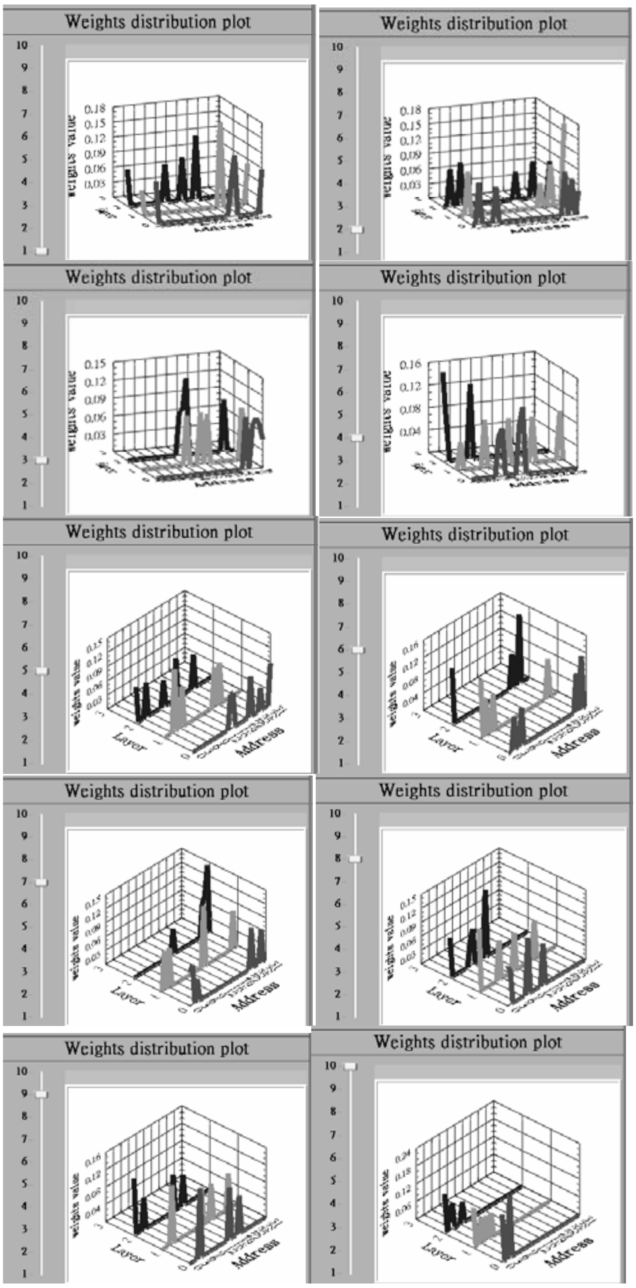

Fig.10 Memory weights distribution plot

are shown in Table 2. As shown in Table 2, output value closed 1 for each degree patterns, denotes the degree type is confirmed undoubtedly.

The test data still shown correct result only row 6 and 7 appear confusion situation. However, we still believe this situation will be improved as the exact pattern collection. It needs more efforts and much time to obtain the desired success.

These results encourage our research and demonstrate the meridian signal reappearance indeed exist for melancholia patients. In our study, even adding 10% to 20% noise to the meridian signals arbitrarily such as T_6 and T_{10} columns, the diagnosis results as shown in Table 4 bold type data, it still confirms what the melancholia degree type is. It guarantees the proposed diagnosis scheme with high feasibility, high accuracy and high noise rejection ability.

However, how to obtain the optimal memory size [10] and to compare the performance difference with other type neural networks [11] is tedious and difficult work. It needs more efforts in future study.

6. PC-based diagnosis system

To facilitate the patterns collection, analyses, and diagnosis, a PC-based diagnosis program is designed and the user interface is shown in Fig. 11. In training mode, user first selects the quantization level q_{max} , training times, learning gain β and noise ratio. Then push the reload and diagnosis button. This program will run the training mode and show the weights distribution plots. Moving the group bar will show the selected group weights distribution plot.

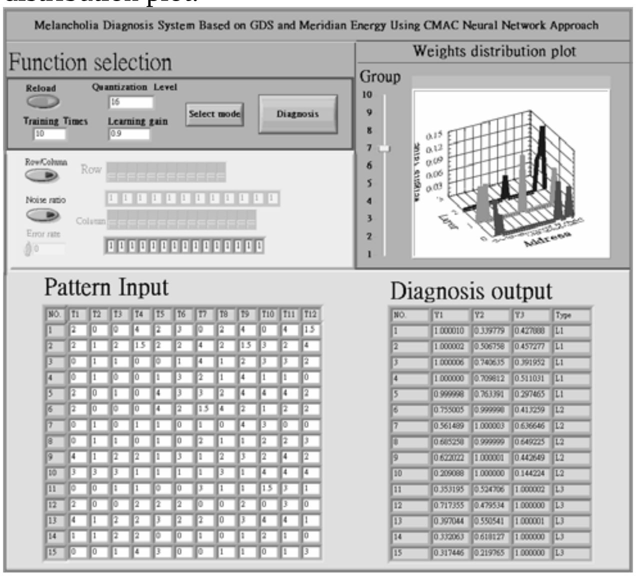

Fig.11 PC based Melancholia diagnosis system interface - training mode

Finished the training mode, then the diagnosis can be used to diagnosis the melancholia degree. In

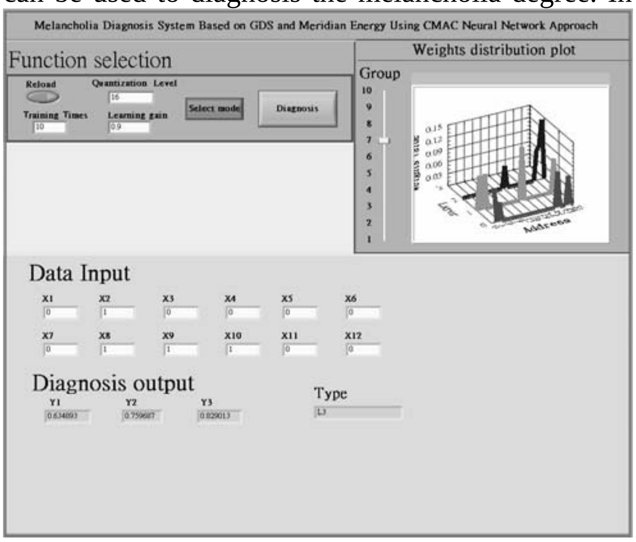

Fig.12 PC based Melancholia diagnosis system interface – diagnosis mode

diagnosis mode, the interface is shown as Fig.12. Inputting the diagnosed data and push the Diagnosis button will show the possible melancholia degree.

5. Conclusion

This work presents a novel melancholia diagnosis scheme combining CMAC NN and energy medicine information. Using the 12 sets meridian energy signal as the input of CMAC NN, the proposed diagnosis system can learn the features of different melancholia degree via training mode and diagnose the possibility of depression degree via diagnosis mode. The preliminary results demonstrate the feasibility of the proposed methodology. Also the friendship diagnosis program is designed in this paper. However, to implement melancholia diagnosis based on CMAC and energy medicine is a long road. It still needs more effort on clinical test and new pattern collection in future.

Acknowledgments

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Table 2. Diagnosis output of pattern and test data.

NO.	CMAC node output			GDS	Depression degree
	L_1	L_2	L_3		
1*	1	0.339	0.427	23	L_1
2*	1	0.506	0.457	23	L_1
3*	1	0.74	0.39	17	L_1
4*	1	0.709	0.511	17	L_1
5*	0.999	0.763	0.297	17	L_1
6	**0.634**	**0.759**	**0.829**	21	L_1
7	**0.596**	**0.643**	**0.275**	17	L_1
8*	0.755	0.999	0.413	9	L_2
9*	0.561	1	0.636	8	L_2
10*	0.685	0.999	0.649	8	L_2
11*	0.622	1	0.442	7	L_2
12*	0.209	1	0.144	7	L_2
13	**0.755**	**0.999**	**0.413**	15	L_2
14	**0.209**	**1**	**0.144**	11	L_2
15*	0.353	0.524	1	6	L_3
16*	0.717	0.479	1	5	L_3
11*	0.397	0.55	1	3	L_3
18*	0.332	0.618	1	0	L_3
19*	0.317	0.219	1	0	L_3
20	**0.266**	**0.304**	**0.838**	7	L_3
21	**0.244**	**0.541**	**0.783**	3	L_3

Table 1: Melancholia pattern* and **test data**

No.	Quantized 12 meridian total energy												GDS	Depression degree
	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}	T_{11}	T_{12}		
1*	2	0	0	4	2	3	0	2	4	0	4	1.5	23	L_1
2*	2	1	2	1.5	2	2	4	2	1.5	3	2	4	23	L_1
3*	0	1	1	0	0	1	4	1	2	3	3	2	17	L_1
4*	0	1	0	0	1	3	2	1	4	1	1	0	17	L_1
5*	2	0	1	0	4	3	3	2	4	4	4	2	17	L_1
6	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**1**	**0**	**0**	**21**	L_1
7	**0**	**2**	**2**	**1.5**	**2**	**1**	**2**	**4**	**2**	**2**	**2**	**4**	**17**	L_1
8*	2	0	0	0	4	2	1.5	4	2	1	2	2	15	L_2
9*	0	1	0	1	1	0	1	0	4	3	0	0	15	L_2
10*	0	1	1	0	1	0	2	1	1	2	2	3	14	L_2
11*	4	1	2	2	1	3	1	2	3	2	4	2	13	L_2
12*	3	3	3	1	1	1	1	3	1	4	4	4	11	L_2
13	**2**	**0**	**0**	**0**	**4**	**2**	**1.5**	**4**	**2**	**1**	**2**	**2**	**15**	L_2
14	**3**	**3**	**3**	**1**	**1**	**1**	**1**	**3**	**1**	**4**	**4**	**4**	**11**	L_2
15*	0	0	1	1	0	0	3	1	1	1.5	3	1	6	L_3
16*	2	0	0	2	2	2	0	0	2	0	3	0	5	L_3
17*	4	1	2	2	3	2	2	0	3	4	4	1	3	L_3
18*	1	1	2	2	0	0	1	0	1	2	1	0	0	L_3
19*	0	0	1	4	3	0	0	1	1	0	1	3	0	L_3
20	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**4**	**0**	**7**	L_3
21	**0**	**0**	**0**	**2**	**0**	**0**	**0**	**0**	**3**	**0**	**2**	**0**	**3**	L_3

Noted: $q_{max} = 16$, training time 10, learning gain 0.9, coding bit 5

Table 3: Geriatric depression rating scale (Long version)

Question	Yes	No
1. Are you basically satisfied with your life?		V
2. Have you dropped many of your activities and interests?	V	
3. Do you feel that your life is empty?	V	
4. Do you often get bored?	V	
5. Are you hopeful about the future?		V
6. Are you bothered by thoughts you can’t get out of your head?	V	
7. Are you in good spirits most of the time?		V
8. Are you afraid that something bad is going to happen to you?	V	
9. Do you feel happy most of the time?		V
10. Do you often feel helpless?	V	
11. Do you often get restless and fidgety?	V	
12. Do you prefer to stay at home, rather than going out and doing new things?	V	
13. Do you frequently worry about the future?	V	
14. Do you feel you have more problems with memory than most?	V	
15. Do you think it is wonderful to be alive now?		V
16. Do you often feel downhearted and blue?	V	
17. Do you feel pretty worthless the way you are now?	V	
18. Do you worry a lot about the past?	V	
19. Do you find life very exciting?		V
20. Is it hard for you to get started on new projects?	V	
21. Do you feel full of energy?		V
22. Do you feel that your situation is hopeless?	V	
23. Do you think that most people are better off than you are?	V	
24. Do you frequently get upset over little things?	V	
25. Do you frequently feel like crying?	V	
26. Do you have trouble concentrating?	V	
27. Do you enjoy getting up in the morning?		V
28. Do you prefer to avoid social gatherings?	V	
29. Is it easy for you to make decisions?		V
30. Is your mind as clear as it used to be?		V
TOTAL GDS		

Table 4: Diagnosis output with random noise.

No.	Quantized 12 meridian total energy												CMAC output			GDS	Degree
	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}	T_{11}	T_{12}	L_1	L_2	L_3		
1*	2	0	0	4	2	**3.3**	0	2	4	**0**	4	1.5	0.809	0.339	0.418	23	L_1
2*	2	1	2	1.5	2	**2.2**	4	2	1.5	**3.6**	2	4	0.721	0.334	0.3	23	L_1
3*	0	1	1	0	0	**1.1**	4	1	2	**3.6**	3	2	0.901	0.691	0.392	17	L_1
4*	0	1	0	0	1	**3.3**	2	1	4	**1.2**	1	0	0.744	0.712	0.363	17	L_1
5*	2	0	1	0	4	**3.3**	3	2	4	**4.8**	4	2	0.832	0.762	0.353	17	L_1
6	0	1	0	0	0	**0**	0	1	1	**1.2**	0	0	0.635	0.76	0.829	21	L_1
7	0	2	2	1.5	2	**1.1**	2	4	2	**2.4**	2	4	0.496	0.521	0.276	17	L_1
8*	2	0	0	0	4	**2.2**	1.5	4	2	**1.2**	2	2	0.666	0.739	0.256	15	L_2
9*	0	1	0	1	1	**0**	1	0	4	**3.6**	0	0	0.535	0.902	0.636	15	L_2
10*	0	1	1	0	1	**0**	2	1	1	**2.4**	2	3	0.597	0.829	0.521	14	L_2
11*	4	1	2	2	1	**3.3**	1	2	3	**2.4**	4	2	0.489	0.717	0.445	13	L_2
12*	3	3	3	1	1	**1.1**	1	3	1	**4.8**	4	4	0.209	0.999	0.144	11	L_2
13	2	0	0	0	4	**2.2**	1.5	4	2	**1.2**	2	2	0.666	0.739	0.256	15	L_2
14	3	3	3	1	1	**1.1**	1	3	1	**4.8**	4	4	0.209	0.999	0.144	11	L_2
15*	0	0	1	1	0	**0**	3	1	1	**1.8**	3	1	0.427	0.524	0.946	6	L_3
16*	2	0	0	2	2	**2.2**	0	0	2	**0**	3	0	0.558	0.392	0.834	5	L_3
17*	4	1	2	2	3	**2.2**	2	0	3	**4.8**	4	1	0.223	0.549	0.773	3	L_3
18*	1	1	2	2	0	**0**	1	0	1	**2.4**	1	0	0.332	0.533	0.797	0	L_3
19*	0	0	1	4	3	**0**	0	1	1	**0**	1	3	0.317	0.219	0.999	0	L_3
20	1	0	1	0	0	**0**	0	0	1	**1.2**	4	0	0.194	0.304	0.838	7	L_3
21	0	0	0	2	0	**0**	0	0	3	**0**	2	0	0.244	0.542	0.783	3	L_3
noise						20%				10%							

Noted: $q_{max} = 16$, training time 10, learning gain 0.9, coding bit 5