Melancholia Diagnosis Based on 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 inventory and the meridian energy of human body is proposed. Firstly, a large amount data obtained from hospital, recorded the patients depression inventory and the 12 sets meridian energy signals, are sieved out three groups patterns. Then, CMAC (Cerebellar Model Articulation Controller) neural network diagnosis architecture is constructed depending on the three groups disease patterns. Thirdly, the selected patterns were utilized to train the CMAC neural network. Finally, inputting the 12 sets meridian energy signals of human body into CMAC neural network, the finished training neural network can diagnose the possibility people with melancholia or not.

Keywords:disease diagnosis, melancholia, depression inventory, CMAC, 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 cure method for these serious diseases. Usually, prophylaxis and diagnosis early 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 endogeneity 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 melancholia in early stages and neglect the diagnosis early until tragedy happened. Unfortunately, melancholia diagnosis is not an easy task. It cannot be made decision by general health 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. The patient must need to fill in depression inventory, such as shown in Table 3, then the doctor evaluate the possibility of melancholia. However, it is not a good diagnosis methodology. The diagnosis correctness strongly depends on does the patient fill in the measure table honestly. Therefore, how to develop a new diagnosis scheme, just like blood test, is the major objective of this paper.

Energy medicine is a new science and technology by measuring and analyzing the 12 sets meridians energy of human body. The 12 sets meridians include lung, pericardium, heart, small intestine, sanjao, large intestine, spleen, liver, kidney, bladder, and gallbladder and stomach meridian. Through a long time research, the standard test points are shown in Figure 1. Energy medicine and traditional Chinese medicine think all the disease can be diagnosed by the 12 sets meridian energy signals. In this paper, we analysis a large amount data, recorded the patients depression inventory 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. 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 diagnosis schemes strongly depend on the clinician-rated behaviorally measurement.

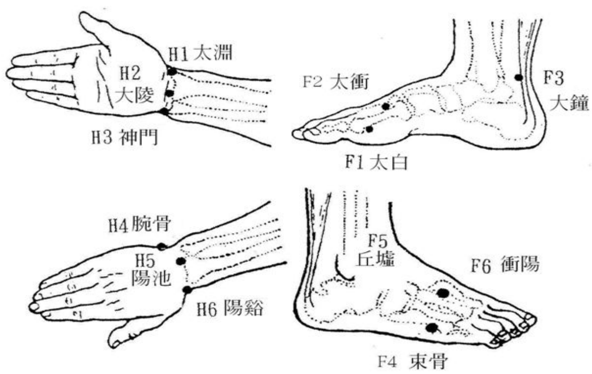

Figure 1: Detection points of meridian energy

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 coding, excited addresses coding and summation of the excited memory weights [4-6]. The characteristic of the mapping processes is that similar inputs excite similar memory addresses; restated, if the input states are close in input space, then their corresponding sets of association 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

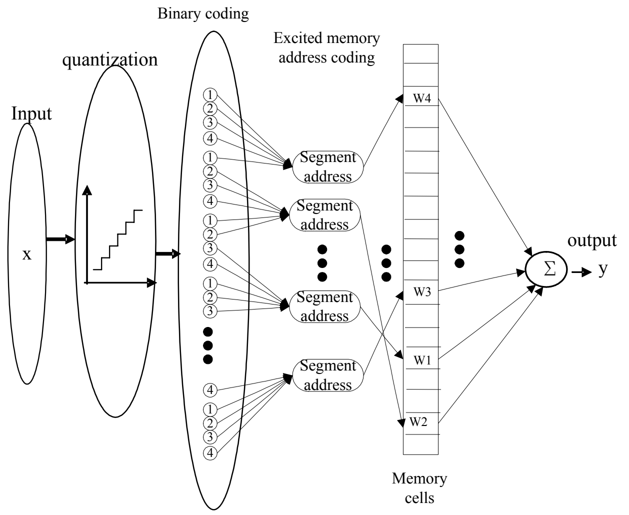

Figure 2: Functional schematic of CMAC neural network

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 distribute the specific signal feature on fired memory addresses. 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 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 patient are the training patterns of the built CMAC diagnosis system.

3. CMAC based melancholia diagnosis system

3.1 pattern collection

In this research, all the melancholia data obtained from Taichung Hospital (in Taiwan). The participated people accepted the depression inventory filling, such as Table 3, and the MEAD (Meridian Energy Analysis Device) energy medicine examination, recorded the meridian energy as Figure 3, simultaneously. Partial data are quantized and rearranged as Table 1. GDS (geriatric depression rating scale) is the melancholia evaluation index based on the depression inventory [8]. Generally, GDS value larger than 20 will be diagnose as severe melancholia patient. In this paper, we sieved out three groups pattern and labeled as F_1, F_2 and F_3. F_1 denotes high possibility with melancholia (severe) and the GDS value larger than 17. F_2 expresses low possibility with melancholia (moderate), GDS value between 10 to 16. F_3, GDS value smaller than 10, represents health people (normal). T_i represents the normalized total meridian energy of the i-th meridian. Generally, the i-th total meridian energy is the average of left and right absolute energy of the i-th meridian.

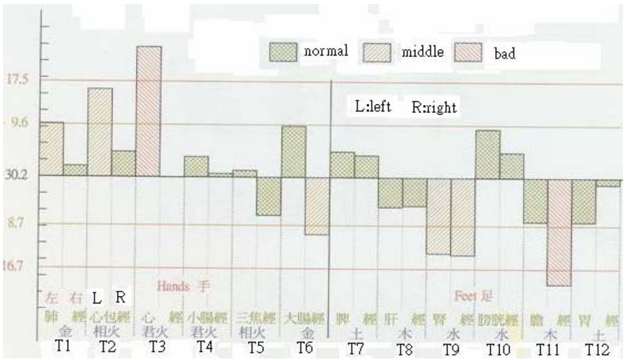

Figure 3: MEAD energy medicine examination report

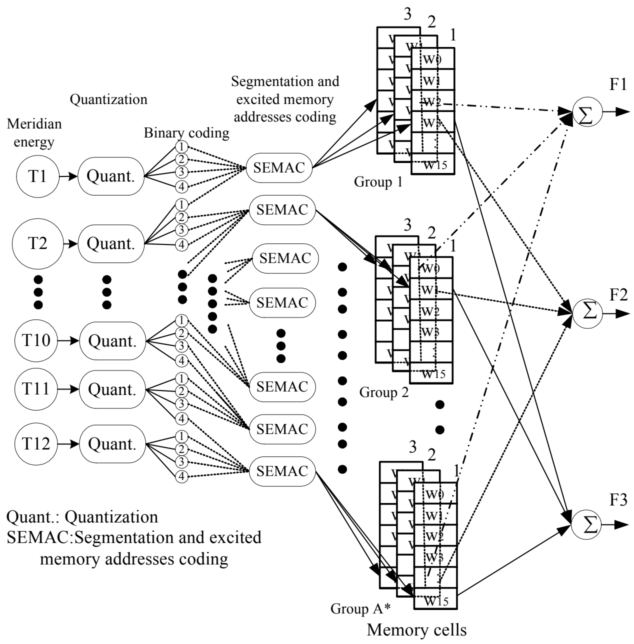

Figure 4: Melancholia diagnosis system using CMAC NN and meridian energy information

3.2 CMAC melancholia diagnosis system

Based on the patterns collection, three melancholia patient level (severe, moderate, normal) and 12 meridians energy inputs, we built the diagnosis architecture as Figure 4. It includes an input layer with 12 input meridian signals, 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 type F_i (i=1,2,3) are used to train the memory layer i which memorizes the feature of melancholia degree F_i only. Inputting the F_i patterns to the diagnosis system, via a series of mappings, including quantization, binary coding, 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 4, 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 [7]

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

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 5, 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.

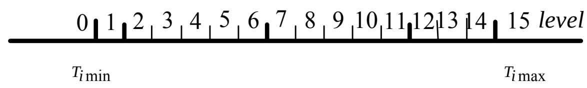

Figure 5: Quantization mapping diagram

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 excited memory addresses coding 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.
011100000000111001111011000001111110000011100110

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 F_i is confirmed, then one can be thought as the teacher and the supervised learning algorithm can be described as [3,4]

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

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 F_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 (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 F_i, it will excite the same memory addresses of layer i and layer i's output near one denotes the melancholia degree type is F_i. But other layer' s output, generally, far away from one expresses a low possibility of melancholia degree F_j ($j \neq i$).Other features of the proposed scheme are described as follows.

3.4 Diagnosis algorithm

Based on the configuration of Figure 4, 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.

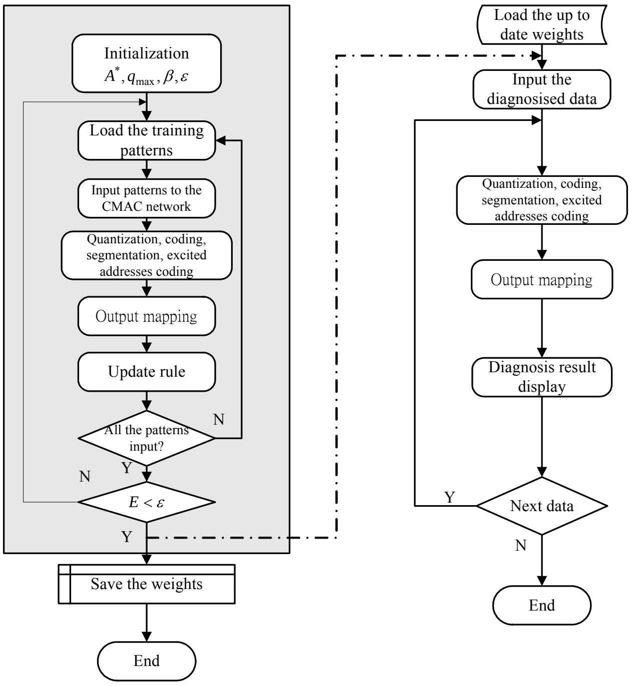

Figure 6: Flowchart of CMAC melancholia diagnosis system

In Figure 6, the left hand side represents the off-line 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 pattern 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, the weights distribution plots of memory layers 1 to 3 for group 2 is shown in Figure 7 after training. Inputting the training patterns and test data to the CMAC diagnosis system again, the diagnosis results are shown in Table 2. As shown in Table 2, output value near 1 for each degree patterns, denotes the degree type is confirmed undoubtedly. The test data still shown correct result only row 6 appears confusion situation. However, we still believe this situation will be improvement as the pattern collection and analysis.

These results encourage our research and demonstrate the meridian signal reappearance indeed exist for melancholia patients. In our study, even adding 10% to 50% noise to the meridian signals, the diagnosis results still confirms what the melancholia degree type is. It guarantees the proposed diagnosis scheme with high feasibility, high accuracy and high noise rejection ability.

5. Conclusion and future work

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. 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
	F_1	F_2	F_3		
1*	1.0088	0.3198	0.4755	23	F_1
2*	0.9991	0.6489	0.3608	23	F_1
3*	1.0054	0.6977	0.4164	17	F_1
4*	0.9994	0.7136	0.4786	17	F_1
5*	0.9987	0.6415	0.4159	17	F_1
6	***0.7034***	0.6332	0.8813	21	F_1
7	***0.5177***	0.5156	0.3056	17	F_1
8*	0.6643	0.9989	0.4074	9	F_2
9*	0.4617	1.0017	0.5879	8	F_2
10*	0.6783	0.9995	0.6574	8	F_2
11*	0.5559	1.0006	0.4899	7	F_2
12*	0.2532	0.9998	0.1809	7	F_2
13	0.6643	0.9989	0.4074	15	F_2
14	0.1830	0.9783	0.1809	11	F_2
15*	0.4503	0.4951	1.0020	6	F_3
16*	0.5677	0.5277	1.0013	5	F_3
11*	0.4492	0.5200	0.9998	3	F_3
18*	0.3368	0.5970	1.0004	0	F_3
19*	0.4153	0.4972	0.9996	0	F_3
20	0.4754	0.2973	***0.9370***	7	F_3
21	0.4394	0.5198	***0.9365***	3	F_3

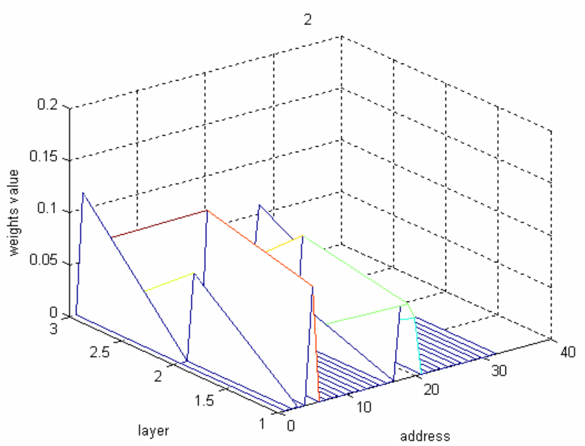

Figure 7: Memory weights distribution plots of group 2

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

No.	Normalized 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	F_1
2*	2	1	2	1.5	2	2	4	2	1.5	3	2	4	23	F_1
3*	0	1	1	0	0	1	4	1	2	3	3	2	17	F_1
4*	0	1	0	0	1	3	2	1	4	1	1	0	17	F_1
5*	2	0	1	0	4	3	3	2	4	4	4	2	17	F_1
6	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**1**	**0**	**0**	**21**	F_1
7	**0**	**2**	**2**	**1.5**	**2**	**1**	**2**	**4**	**2**	**2**	**2**	**4**	**17**	F_1
8*	2	0	0	0	4	2	1.5	4	2	1	2	2	15	F_2
9*	0	1	0	1	1	0	1	0	4	3	0	0	15	F_2
10*	0	1	1	0	1	0	2	1	1	2	2	3	14	F_2
11*	4	1	2	2	1	3	1	2	3	2	4	2	13	F_2
12*	3	3	3	1	1	1	1	3	1	4	4	4	11	F_2
13	**2**	**0**	**0**	**0**	**4**	**2**	**1.5**	**4**	**2**	**1**	**2**	**2**	**15**	F_2
14	**3**	**3**	**3**	**1**	**1**	**1**	**1**	**3**	**1**	**4**	**4**	**4**	**11**	F_2
15*	0	0	1	1	0	0	3	1	1	1.5	3	1	6	F_3
16*	2	0	0	2	2	2	0	0	2	0	3	0	5	F_3
17*	4	1	2	2	3	2	2	0	3	4	4	1	3	F_3
18*	1	1	2	2	0	0	1	0	1	2	1	0	0	F_3
19*	0	0	1	4	3	0	0	1	1	0	1	3	0	F_3
20	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**4**	**0**	**7**	F_3
21	**0**	**0**	**0**	**2**	**0**	**0**	**0**	**0**	**3**	**0**	**2**	**0**	**3**	F_3

Table 3: Geriatric depression rating scale (SHORT version)

Question	Yes	No
1. Are you basically satisfied with your life?		
2. Have you dropped many of your activities and interests?		
3. Do you feel that your life is empty?		
4. Do you often get bored?		
5. Are you in good spirits most of the time?		
6. Are you afraid that something bad is going to happen to you?		
7. Do you feel happy most of the time?		
8. Do you often feel helpless?		
9. Do you prefer to stay at home, rather than going out and doing new things?		
●●●		
TOTAL GDS		