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Research Article

EMG Signal Analysis for Diagnosis of Hansen Disease using Neural Network

Manoj Singh Rajput[Å*], Rameshwar Singh[Å], S.S.Dhakad[Å] and A.S.Trivedi[Å]

[Å]Department of Electrical Engg., Nagaji Institute of Technology & Management, Gwalior (M.P.), India

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Abstract

Electromyography (EMG) provides useful information for diagnosis. This paper deals with a computer based expert system which has been developed for the diagnosis of HD using the features of EMG signal recorded from the disease site. In this study frequency domain parameters of the EMG signal and signal under both the healthy and leprosy conditions of the subjects for the disease diagnosis using an artificial neural network.

Keywords: *EMG signal, Hansen disease etc.*

1. Introduction

EMG signals have a frequency rang from 2 Hz to 10Hz. Merletti et al and other researchers have concluded that the EMG signals collected through the surface electrodes do not have significant components above 450 Hz in the Hansen disease (George RV et al, 2008) .Manual measurement and analysis are time consuming processes and introduce various type of errors. Therefore, to handle a large amount of data and clinical important parameters, computer aided diagnostic procedures are the best solution for the measurement. The features of the EMG signal indicate the health of muscle fibers, motor units, motor neurons and the muscles. Signal is recorded by inserting a small needle electrode or by putting a surface electrode on the muscle.

2. Parameters of Diagnosis

Different workers have taken different clinical important parameters for the diagnosis of HD such as RMS value, average value and form factor of decomposition EMG signal, median frequency, power at median frequency, maximum frequency, autocorrelation, cross correlation function and maximum power. After analyzing it was found that RMS value of the decomposed signal, power at median frequency and maximum power show clear-cut difference in healthy and leprosy muscles. Median frequency shows slight difference between healthy and leprosy muscles. In the present work, one more parameter i e 'area under the power spectrum curve' have been taken as an additional clinically important parameter. It has been found that this parameter gives significance different between healthy and leprosy cases. It can be summarized frequency domain parameter provide useful information for diagnosis of HD case (Kai M et al, 2011; Anderson H et al, 2007; Walker SL et al, 2007).

*Corresponding author **Manoj Singh Rajput** is a PG student; **Rameshwar Singh** and **S.S.Dhakad** are working as Assistant Professors; **A.S.Trivedi** as Professor

3. Neural Network based Diagnostic System

The system consist of an EMG data acquisition and processing unit (to determine RMS value of the EMG signal using wavelet), feature extraction unit (for frequency domain parameter) fuzzification unit and interfacing unit (for the disease identification). Three independent interpretations of the diseases available on the basis of the RMS value of the EMG signal using wavelet, frequency domain parameter are the final diagnostics in the category of healthy, leprosy (borderline, clear-cut, severe) cases. Figure 1 show the block diagram of the neural network based diagnostic system.

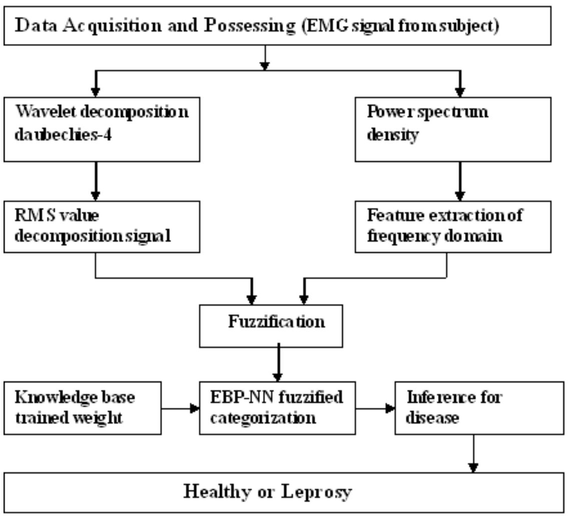

Fig. 1: Block Diagram of Expert System

4. Clinical Important Parameters

Different workers have taken different clinical important parameters for the diagnosis of HD such as RMS value and from factor of the decomposition EMG signal, median frequency, power at median frequency, maximum frequency, autocorrelation, cross-correlation function and maximum power. After analyzing it was found that RMS value of the decomposition signal, power at median frequency and maximum power show clear-cut difference in leprosy &healthy muscles. Median frequency shows slight difference for leprosy cases. Average value and from factor of the decomposed signal, autocorrelation function and cross-correlation function were not showing the difference between healthy & leprosy muscle. In the present work, one more parameter i e ‘area under power spectrum curve’ have been taken as an additional clinically important parameter. It has been found that this parameter gives significant difference between healthy and leprosy cases. It can be summarized that the following parameters provide useful information of HD cases (A Mangora et al, 1965; G Favieiro et at, 2011; J G Hincapie et al, 2009)

5. Decomposition of Signal

Five decomposition using dB-4 wavelet, is calculated by using the following RMS value of decomposed signal: the RMS value of decompose signal and its equation

$$x_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}[x(n)]^2} \qquad (1.1)$$

Where, n is the number of sample and x (n) is the discrete time signal.

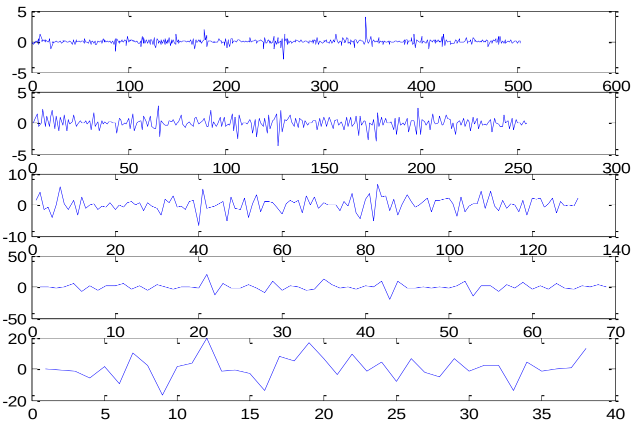

Fig. 3: Wavelet Decomposition Signal for Healthy Subject

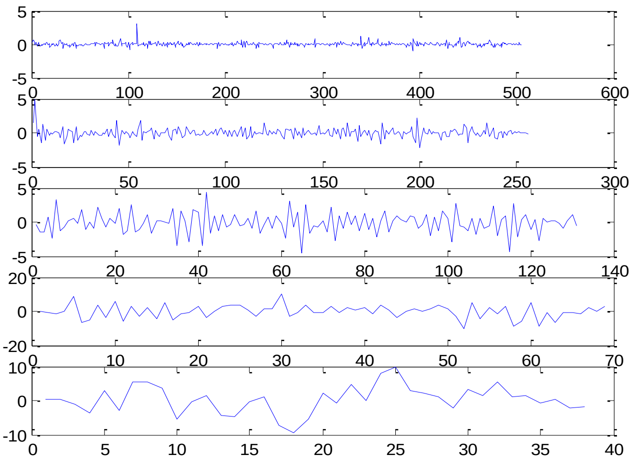

Fig. 2: wavelet decomposition signal for leprosy subject

RMS value of the Decomposition signal: The RMS value of all five decomposition is using db-4 were obtained for healthy as well as leprosy cases are shown in table. It is observed that, in all the above five decomposition, 3rd, 4th, and5th decompositions show significant difference between healthy and leprosy cases.

Table 1 Rms value of the muscle using db-4 wavelet in micro-volts

Subj. no.	Original	Ist	IInd	IIIrd	IVth	Vth
1	2.33	0.44	1.22	3.78	5.31	4.05
2	3.10	0.72	1.58	5.04	7.64	6.2
3	2.59	0.42	0.90	2.19	5.9	7.6
4	3.39	0.7	1.68	4.52	8.22	6.54
5	0.11	0.35	0.89	1.83	1.10	2.62
6	1.58	0.28	0.70	1.54	3.86	2.05
7	0.83	0.19	0.40	0.8	1.83	1.83
8	1.27	1.10	1.28	1.09	1.125	1.02
9	2.37	0.42	0.76	1.81	2.26	2.40
10	1.77	0.37	0.95	2.50	3.65	2.88

6. Frequency Domain Parameter

Frequency domain feature like median frequency, power at median frequency, maximum frequency maximum power and area under curve of the EMG signal provide additional information in the assessment of leprosy. These parameters reflect the changes taking places inside the muscle and muscle fibers.
The features extractions:

(1)Median frequency: Median = Middle value of a set of data. The frequency at which the power spectrum is divided into two regions of equal power. The median is the point at which exactly half of the data are above and half below. These halves meet at the median position.

Remember that n represents the number of values in the data set.

Median = (n + 1) ÷ 2th value

Since there is an even number of observations in this data set, there is no longer a distinct middle value.

Use the formula below to get the average value.

Average = (value below median + value above median) ÷ 2

(2) Power at median frequency

It is define as power spectral estimate at median frequency.

(3) Maximum frequency

It is calculate as the frequency at which the power at maximum.

(4) Maximum power

It is the maximum power of signal.

(5) Area

It is area under the power spectrum

$$Area = \sum_{i=1}^{n-1} y_i * x_i \qquad (1.2)$$

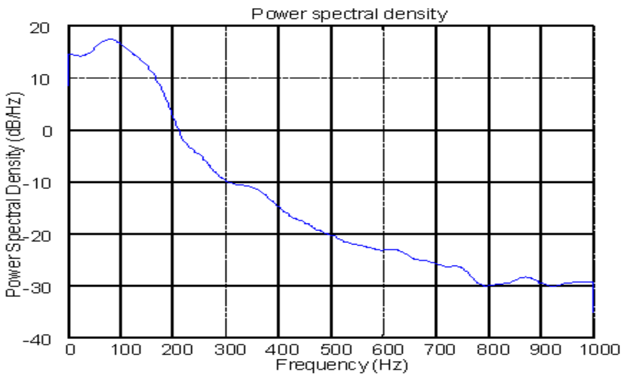

Fig. 4: EMG and power spectrum density for healthy case

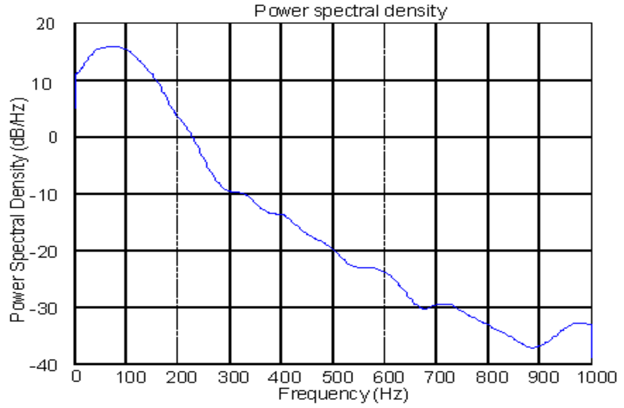

Fig. 5: EMG and power spectrum density for leprosy case

Table 2 Frequency domain parameters of EMG signal

Subject no.	Median freq. Hz	Max. freq. Hz	Median power volt	Max. power volt	Area volt sec
1	103.38	35.86	31.4	60.03	1823.28
2	112.5	93.75	20.86	43.4	2200.8
3	64.0	22.00	5.6	82.00	1075.04
4	80.79	12.03	20.79	130.08	3100.8
5	69.79	65.80	3.5	12.00	450.0
6	28.0	2.0	0.5	15.78	44.12
7	96.3	2.0	0.8	4.5	273.26
8	48.59	2.0	4.7	25.1	159.1
9	50.78	39.06	1.00	11.2	210.42
10	69.79	65.80	3.5	12.00	450.0

7. Knowledge Base Domain (KB)

The knowledge acquisition system is capable of acquiring information on medical entities and the relationships between them. The relationships are stored as numerical values in the range 0 to 1. Medical information is acquired in two ways (1) through numerical or linguistic evaluation by medical experts, and (2) by statistical evaluation of a database containing medical data on patients with confirmed diagnosis. The information on the relationship can be gathered numerically or linguistically using predefined linguistic values to determine parameters, such as frequency of occurrence and strength of confirmation. In the expert system, the knowledge has been acquired using both the ways. The KB is the heart of expert system as it provides the standard RMS values and frequency domain parameter for healthy and leprosy cases. Proper design and implementation of KB significantly affect the performance of the expert system. These values for KB are shown in Tables3 and 4 (P Palmes et al, 2010; A Mangora et al, 1965).

Table 3 RMS value of the EMG signal for healthy and leprosy cases in micro-volts

R.M.S. value of EMG signal db-4	Healthy			Leprosy		
	L	M	U	L	M	U
After 3rd decomposition.	2.19	3.7	5.04	0.8	1.54	2.50
After 4th decomposition.	5.3	7.6	8.22	1.12	2.05	4.10
After 5th decomposition.	4.05	6.54	7.6	1.02	1.83	2.88

Table 4.1 Frequency domain EMG parameter

Subject	Median frequency Hz			Power at median frequency volt^2			Frequency at maximum at power Hz		
	L	M	U	L	M	U	L	M	U
Healthy	64	80	112	5.6	20	31.4	14	30	54
Leprosy	28	48	96	0.5	1.0	4.7	2	30	46

Table 4.2 Frequency domain EMG parameter

Subject	Maximum power at volt^2			Area under power spectrum curve volt^{2}sec		
	L	M	U	L	M	U
Healthy	43.3	82	130	1075	2200	3100
Leprosy	4.5	12	25.1	44	303	450

The KB acquires information on all medical entities to establish the relationships amongst all the parameters, the lower, mean and upper value of RMS values and frequency domain parameters have been used as the standard values of healthy and leprosy cases for classification. The median frequency, power at median frequency, frequency at median power and area under the power spectrum curve are the indicator of the spectral changes.

8. EMG signal classification

The dB-4 gave clear distinction between the healthy and leprosy cases and took less computation time, it was also seen that dB-4 is localized in frequency domain. however, for RMS value, or aim is to distinguish between the frequency components of the signal, therefore dB-4 wavelets proved to be more useful, the measured RMS values using dB-4 and frequency domain parameter from subject are fuzzified and their corresponding numeric values, assigned to linguistic term, are given as input to EBP-NN and are shown in Table 7 (Pratesh Jayaswal et al, 2010).

Table 5 Fuzzification of parameters and corresponding numeric values for input to EBP-NN

(1) Median Frequency (MF)

S.N.	Range Hz	Degree of severity	Numeric Value
1	MF≤28	LEPROSY-SEV	0.9
2	28<MF≤50	LEPROSY-CC	0.7
3	50<MF≤65	LEPROSY-BL	0.5
4	MF>65	HEALTHY	0.1

(2) Power at Median Frequency (MDP)

S.N.	Range Hz	Degree of severity	Numeric Value
1	MDP≤1	LEPROSY-SEV	0.9
2	1<MDP≤3	LEPROSY-CC	0.7
3	3<MDP≤6	LEPROSY-BL	0.5
4	MDP>6	HEALTHY	0.1

(3) Frequency at Maximum Power (MXF)

S.N.	Range Hz	Degree of severity	Numeric Value
1	MXF≤2	LEPROSY-SEV	0.9
2	2<MXF≤10	LEPROSY-CC	0.7
3	10<MXF≤30	LEPROSY-BL	0.5
4	MXF>30	HEALTHY	0.1

(4) Maximum Power (MXP)

S.N.	Range Hz	Degree of severity	Numeric Value
1	MXP≤10	LEPROSY-SEV	0.9
2	10<MXP≤26	LEPROSY-CC	0.7
3	26<MXP≤45	LEPROSY-BL	0.5
4	MXP>45	HEALTHY	0.1

(5) Area under Power Spectrum Curve (A)

S.N.	Range Hz	Degree of severity	Numeric Value
1	A≤200	LEPROSY-SEV	0.9
2	200<A≤800	LEPROSY-CC	0.7
3	800<A≤1050	LEPROSY-BL	0.5
4	A>1050	HEALTHY	0.1

(6) RMS value of the signal using dB-4

(i) After 3rd decomposition

S.N.	Range Hz	Degree of severity	Numeric Value
1	RMS≤0.8	LEPROSY-SEV	0.9
2	0.8<RMS≤1.54	LEPROSY-CC	0.7
3	1.54<RMS≤2	LEPROSY-BL	0.5
4	RMS>2	HEALTHY	0.1

(ii) After 4th decomposition

S.N.	Range Hz	Degree of severity	Numeric Value
1	RMS≤1.12	LEPROSY-SEV	0.9
2	1.12<RMS≤4.1	LEPROSY-CC	0.7
3	4.1<RMS≤5	LEPROSY-BL	0.5
4	RMS>5	HEALTHY	0.1

(iii) After 5th decomposition

S.N.	Range Hz	Degree of severity	Numeric Value
1	RMS≤1	LEPROSY-SEV	0.9
2	1<RMS≤2.88	LEPROSY-CC	0.7
3	2.88<RMS≤4	LEPROSY-BL	0.5
4	RMS>5	HEALTHY	0.1

The output of the EBP-NN are in the form of '0'and'1'.all possible combinations of 0's and1's are taken into consideration as shown in Table 8,. The output layer has to nodes; 1st node for healthy case, 2nd and 3rd nodes for leprosy diseased cases.

Table 5 Output Nodes

S.N.	State of Muscle	Node 1	Node 2	Node 3	Severity
1	Healthy	0	0	0	-
2	Leprosy	1	0	0	Borderline
		1	1	0	Clear-cut
		1	1	1	Severe

A two layer EBP-NN having nodes at the input and three nodes at the output has been trained by taking the various combinations of nodes in the first and second hidden lavers and different values of the learning rate and momentum factor. Several trials were made for large number of iterations. It was found that 8-4-3-3 EBP-NN model gives the best result with learning rate equal as 0.2 and momentum factor as 0.4 and the resulting average error is of the order of 0.000047 in the diagnosis of various category of disease. The crucial characteristic of the NN is that it can learn by example to perform useful tasks. This is usually achieved by using teaching algorithms that iteratively modifies the network weights until it responds as desired to set of input patterns in the process of supervised learning. The network trained by 10 input sets and tested with 21 output sets.

- Type of neural network: EBP-NN
- The No of input nodes:8
- The no. of Hidden layers:2
- The no of nodes in each hidden layer:7
- No of output nodes:3
- The learning rate : 0.2
- The momentum factor: 0.4
- The no of epochs:10,000
- Error:0.00047

9. Final Disease Diagnosis Decisions

It is a complex and partly uninvestigated process in which system is obviously able to work uncertain and imprecise sets of possibilities. Type of leprosy and its severity are defined in the final stage of the healthy, borderline, clear-cut and severe as shown in the above output is then compared with the output of neural network for the final disease diagnostics. Following IF-THEN rules are used for final decision.

Table 6 Four categories for output of final decisions

	Lower limit	Upper limit
Healthy	-	<0.1
Borderline	>0.1	<0.5
Clear-cut	>0.5	<0.1
Severe	>0.1	-

Conclusion

The system has been successfully developed and tested for the diagnosis of leprosy case using the features of the EMG signals. The qualitative information from the subject and quantitative information from the EMG signal can be successfully used for the diagnosis of the Hansen disease (leprosy).This approach is reliable and provides wide spread of information to help the physician in reaching a more logical conclusion for a more accurate diagnosis. This method can prove valuable aid in an early and accurate diagnosis of leprosy disorder on the basis of the changes in the EMG signal.

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