A DIFFERENT METHOD TO THE DIAGNOSIS OF GASTRIC DYSRHYTHMIA FROM THE ELECTROGASTROGRAM

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Abstract: Electrogastrogram (EGG) is the cutaneous recording of gastric electrical activity. Its main component, gastric slow wave's normal frequency is in the 2-4 cpm range. Abnormality in this frequency is called gastric dysrhythmia. Gastric dysrhythmia has been frequently observed in patients with gastric motility disorders, gastrointestinal symptoms, such as nausea, vomiting, abdominal pain and diabetic gastroparesis. Diabetic gastroparesis is commonly present in long-standing insulin-dependent diabetes mellitus.

The aim of this study was to develop an automated assessment method to diagnose of gastric dysrhythmia from the Electrogastrogram of diabetic gastroparesis patients. The method proposed based on Discrete Wavelet transform (DWT) and Artificial Neural Network (ANN).

Introduction

Gastrointestinal motility is the combination of two activities: movement of food from the mouth to the anus and mixing of food by breaking it into uniformly small particles [1]. After feeding, the contractile activity of the stomach helps to mix, grind and eventually evacuate small portions of chyme into the small bowel, while the rest of the chyme is mixed and ground. With the accomplishment of the whole digestive process of the stomach, a spatiotemporal pattern is formed [2]. It is called gastric myoelectrical activity. Normal gastric myoelectrical activity consists of a slow wave and spike potentials. Its main component, gastric slow wave controls the velocity and propagation of gastric contractions [3].

The electrogastrogram (EGG) is a cutaneous recording of gastric myoelectrical activity using abdominal electrodes [4]. The dominant frequency of EGG is 0.05Hz or 3 cycles per minute (cpm) [5].

Disturbances of the EGG (gastric dysrhythmias) can occur different patterns [6] as follows: an increase in the dominant frequency of the myoelectrical activity of the stomach from 3cpm to 4 – 9cpm regular activity is defined as tachygastria, a decrease in the dominant frequency of the myoelectrical activity of the stomach from 3cpm to 1 – 2cpm regular activity is defined as bradygastria. Gastric dysrhythmia has been frequently observed in patients with gastric motility disorders, gastrointestinal symptoms, such as nausea, vomiting, and diabetic gastroparesis [7-8]. The use of EGG has been most widely studied in patients with gastroparesis. Symptoms include bloating, distension, nausea, and vomiting. When severe and chronic, gastroparesis can be associated with poor nutritional status and poor glycemic control in diabetics [9].

Unlike other surface electrophysiological recordings,EGG is a lower amplitude signal compared, hence the signal-to-noise ratio of cutaneous EGG is low [10]. Without any noise, a pure EGG is a weighted summation of all internal electrical activities in the stomach [11] and also EGG contains noise, such as respiratory, motion artifacts and the ECG [12]. In addition, EGG is a nonstationary signal. Its properties such as frequency, amplitude, phase, etc., in the slow waves change with time and subject's health condition [6]. Any signal processing performed on the EGG signal must therefore be suitable for nonstationary signals.

Discrete Wavelet transform (DWT) was designed for nonstationary signals since it incorporates the concept of scale into the transform, which gives better time-frequency resolution: a compressed wavelet for analyzing high frequency details and a dilated wavelet for detecting lower frequency underlying trends [13].

A number of successful applications of Artificial Neural Network (ANN) to biomedical signal detection and pattern recognition have been reported, including estimation of the ejection fraction of a human heart, diagnosis of cardiac arrhythmias, identification of corrupted arterial pressure signal, and classification of human chromosomes [14-19]. The problems of the EGG in clinical applications are perfect candidates for ANN. While the EGG may have different characteristics during motor quiescence and gastric contractions, no mathematical algorithms or 'if-then' statements can be made to distinguish the EGG. However, a large amount of data can be easily made available due to the non-invasive nature of the EGG techniques [20].

The aim of this study was to develop an automated assessment method to diagnose of gastric dysrhythmia from the EGG of diabetic gastroparesis patients. The method proposed in this paper was based on DWT and ANN. First, the EGG signal was decomposed into details and approximation coefficients using DWT. Second we obtained power spectral density of these coefficients which was used as the input to an ANN.

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The power spectral densities indicate the power density of the EGG among different frequency subbands. The computation of the power spectral densities of subband signals is more accurate than the computation of the subband signals[21]. Therefore, we used power spectral densities as the input to the ANN. The ANN was trained to classify the EGG into two categories: normal and gastric dysrhythmia.

Materials and Methods

EGG signals were participated from 36 healthy volunteers and 66 diabetic gastroparesis patients. The healthy volunteers were with no past history of gastric dysrhythmic diseases. All of the diabetic gastroparesis patients had previously established diagnosis of the delayed gastric emptying

The EGG recording performed in a quiet room. They were asked not to talk and not to move in order to avoid motion artifacts. Three electrodes were placed over on the abdominal skin [11]. Two active electrodes were positioned below the left costal margin and between the xyphoid process and umbilicus. The reference electrode positioned in the right upper quadrant.

EGG signal acquisition was conducted by Biopac Sys. MP100WSW unit in the nuclear medicine department of Erciyes University hospital. The serial output of EGG recorder device unit was sampled at 200 samples/sec .

DWT is used for the extraction of frequency features from the EGG by decomposing the signal into multiple frequency subbands. All wavelet transforms can be specifed in terms of a low-pass filter h, which satisfes the Standard quadrature mirror filter condition:

$$H(z)H(z^{-1}) + H(-z)H(-z^{-1}) = 1 \quad (1)$$

where H(z) denotes the z-transform of the filter h. Its complementary high-pass filter can be defined as

$$G(z) = zH(-z^{-1}). \quad (2)$$

A sequence of filters with increasing length (indexed by i) can be obtained.

$$H_{i+1}(z) = H(z^{2^i})H_i(z) \quad (3)$$

$$G_{i+1}(z) = G(z^{2^i})H_i(z), \ i = 0, \dots, I-1 \quad (4)$$

with the initial condition $H_0(z) = 1$. It is expressed as a two-scale relation in time domain

$$\begin{aligned} h_{i+1}(k) &= [h]_{\uparrow 2^i} * h_i(k), \\ g_{i+1}(k) &= [g]_{\uparrow 2^i} * h_i(k), \end{aligned} \quad (5)$$

where the subscript $[\cdot]_{\uparrow m}$ indicates the up-sampling by a factor of m and k is the equally sampled discrete time.

The normalized wavelet and scale basis functions $\varphi_{i,l}(k)$, $\psi_{i,l}(k)$ can be defined as

$$\begin{aligned} \varphi_{i,l}(k) &= 2^{i/2} h_i(k - 2^i l), \\ \psi_{i,l}(k) &= 2^{i/2} g_i(k - 2^i l), \end{aligned} \quad (6)$$

where the factor $2^{i/2}$ is an inner product normalization, i and l are the scale parameter and the translation parameter, respectively.

The discrete wavelet transform decomposition can be described as

$$\begin{aligned} s_{(i)}(l) &= x(k) * \varphi_{i,l}(k), \\ d_{(i)}(l) &= x(k) * \psi_{i,l}(k), \end{aligned} \quad (7)$$

where $s_{(i)}(l)$ and $d_i(l)$ are the approximation coeficients and the detail coeficients at resolution i, respectively [22].

In the present study, EGGs were decomposed with 'db3' Daubechies Wavelets to the fourth level. Power spectral density calculations for each of these signals were made using Welch method. Hanning window of 256 samples with an overlap of 128 samples are used. We made the spectral estimate with Welch's Method, which can be expressed as follows [23]:

$$\tilde{P}_{per}(\omega) = \frac{1}{MUL} \sum_{i=1}^{L} \left| \sum_{n=0}^{M-1} x_N^i(n) W(n) e^{-j\omega n} \right|^2, \quad (8)$$

where

$$x_N^i(n) = x_N[n + (i-1)M], \quad 0 \leqslant n \leqslant M-1, \ 1 \leqslant i \leqslant L, \quad (9)$$

$$U = \frac{1}{M} \sum_{n=0}^{M-1} W^2(n), \quad (10)$$

Where $x_N(n)$ is the signal of length N and is divided into L sections with length M overlapping each other, $x^i_N(n)$ is the number i section of $x_N(n)$; W(n) is the window function of length M [24]. Power spectral density graphics for healthy and gastric dysrhythmic subjects can be seen in Figures 1 and 2 respectively.

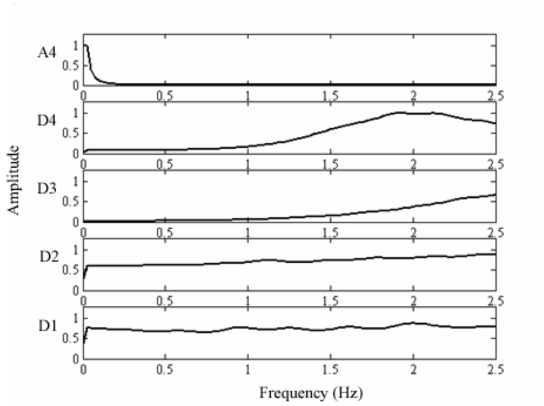

Figure 1: Power spectral density graphics of a decomposed healthy EGG

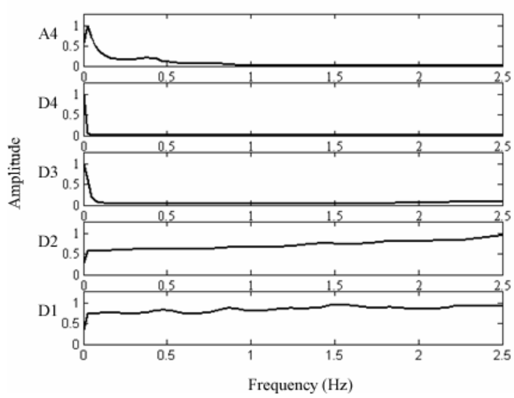

Figure 2: Power spectral density graphics of a decomposed gastric dysrhythmic EGG

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ANN is an information processing system where information spreads parallel on. The most important thing about ANN is that it works as an expert system which will eventually help the physicians with the decision making process about the existence of the diseases. Multilayer feed forward ANN was implemented in the Matlab environment. This choice is appropriate for solving pattern classification problems where supervised learning is implemented with a Leverberg-Marquart (LM) backpropagation algorithm. In this study, a LM backpropagation neural network is used for the interpretation of EGG waveforms. The advantage of using this type of ANN is the rapid execution of the trained network, which is particularly advantageous in signal processing applications [21]. The network is iterated for single and double hidden layers with combinations of one to ten neurons in each layer. For each layer combination, the target mean square error was set to 0.0000001 and the epoch number was taken as 25. The train input data set consists of 25 healthy and 35 diabetic gastroparesis patients, while the test data set was made of 11 healthy and 31 diabetic gastroparesis patients. The minimum training and testing errors were accomplished with the combination of double hidden layers consisting of twenty five and ten consecutively. Each hidden layer sigmoidal function and output layer linear function was used (Figure 3).

The performance of the ANN algorithms were assessed by the following measures [25]

True Positive (TP): The ANN identifies an input as a gastric dysrhythmia that was labeled as a gastroparesis patient by the expert.

True Negative (TN): The ANN identifies an input as a normal that was labeled as a healthy by the expert.

False Positive (FP): The detection of a dysrhythmia in an EGG segment that was labeled as a normal by the expert.

False Negative (FN): The detection of a rhythmic activity in an EGG segment that was labeled as a gastroparesis patient by the expert.

The performance of the classifier is also assessed in terms of sensitivity and specificity as follows;

Sensitivity (SEN): A measure of the ability of the classifier to detect dysrhythmic activities.

Sensitivity = (TP)/(TP+FN) %

Specificity (SPE): A measure of the ability of the classifier to specify normal activities.

Specificity = TN/(TN+FP) %

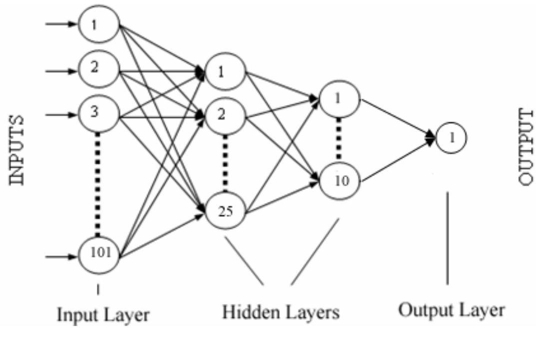

Figure 3: Structure of ANN

Results

In this study, we used DWT for feature extraction. It was calculated averaged Power Spectral Density (PSD) from DWT coefficients (A4, D1-D4) for 36 healthy volunteers and 66 diabetic gastroparetic patients. Power spectral densities of the DW coefficients were used to train and test the network. And, the back-propagation artificial neural network, we built from logarithmic sigmoid neurons and trained with LM has demonstrated to provide excellent gastric dysrhythmia classifying results. The four layered MLP structure that we have built had given very promising results in classifying the healthy and gastric dysrhythmia. Testing mean square error of 0.0236 was observed for our optimized MLP feed forward network with training mean square error of $5.7492*10^{-8}$. As seen in Table 1, 94-98 % success rate of classification was accomplished with the designed feature extraction and the neural network structures.

Table 1: Testing results of the trained ANN

Group Type	Real Number of Subjects	True	False
Negative	36	35	1
Positive	66	64	2
TOTAL	102	99 (%97)	8 (%3)
Sensitivity = %98.5			
Specifity= %94.5			

Discussion

The training and testing of the network demonstrated the accuracy of the proposed automatic classification method. While this paper provides a new and alternative method for the classification of the EGG, it should be noted that the accuracy of this method is associated with the EGG recording and spectral analysis method applied for the training of the ANN. EGG is a nonstationary signal so we use DWT analysis to get most accurate results. When properly recorded, the EGG is a reliable measurement of the frequency of the gastric slow wave. Therefore, during the recording, every effort should be made to assure the highest possible signal-to-noise ratio. These include appropriate preparation of the skin and placement of the electrodes, minimization and elimination of motion artifacts, etc.

Conclusions

We have presented a new method for the automated classification of the EGG based on DWT and ANN. In our study, DWT is used for the extraction of frequency features from the EGG by decomposing the signal into details and approximation coefficients. This method is new to the field of electrogastrography. The computation of the signal energy in the details and approximation coefficients is more accurate than the computation of signal energy based on the power spectral density. Although the automatic assessment of the regularity of the EGG is difficult because of its poor

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signal-to-noise ratio, the ANN is introduced for the automated classification of the EGG. Because the ANN has the ability to learn functionality where it is possible to specify the inputs and outputs but difficult to define their relationship [40, 41]. It is tolerant to noise in the input data [21]. These attributes of the ANN are suitable for the assessment of the EGG.

In conclusion, the method proposed in this paper provides an automatic and time saving procedure for the classification of the EGG. We believe that we developed an expert system for the interpretation of the EGG signals using ANN. The stated results show that the proposed method can make an effective interpretation. If this method is to be used as a standard classification tool, general consensus must be reached among investigators on the EGG classification rules used to train the ANN.

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