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Med. Eng. Phys. Vol. 17, No. 3, pp. 219–225, 1995

1350-4533/95 $10.00 + 0.00

Non-invasive identification of gastric contractions from surface electrogastrogram using back-propagation neural networks

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Received September 1993, accepted April 1994

ABSTRACT

Gastric contractions play an important role in the digestive process of the stomach. The established method for the measurement of gastric contractions is invasive and involves the insertion through the nose of a manometric probe into the stomach. A non-invasive method is introduced in this paper for the identification of gastric contractions using the surface electrogastrogram. The electrogastrogram (EGG) was measured by placing surface electrodes on the abdominal skin over the stomach in ten subjects. Gastric contractions were simultaneously monitored using an intraluminal manometric probe. The back-propagation neural network was applied to identify gastric contractions from the EGG. The input of the neural network was composed of spectral data points of the EGG which was computed using the exponential distribution method. Experiments were conducted to optimize network structures and parameters. Using the EGG data in five subjects as the training set and the EGG data in another five subjects as the testing set, an overall accuracy of 92% was achieved in the identification of gastric contractions with an optimized three-layer back-propagation neural network (number of nodes for input:hidden:output layers being 64:10:2).

Keywords: Neural networks, signal processing, electrogastrogram, gastric motility, stomach

Med. Eng. Phys., 1995, Vol. **17**, 219–225, April

INTRODUCTION

Gastric motility plays an important role in the digestive process of the stomach. In the fasting state, there is a cyclical motor activity called the migrating motor complex (MMC)[1,2]. Each complex is characterized by the cyclical occurrence of motor quiescence (Phase I), seemingly random contractions (phase II) and maximum contractile activity (Phase III). The MMC serves as an 'intestinal housekeeper' that empties non-digestible contents from the stomach into the small intestine. In the postprandial state, there are phasic contractions propagating distally which lead to gastrointestinal peristalsis.

Gastric contractions can be measured mechanically by intubating the stomach with a probe containing pressure sensors or myoelectrically by placing electrodes on the mucosal or serosal surface of the stomach[3,4]. However, all these methods are invasive and so tend not to be carried out in patients who already have gastrointestinal motor disorders.

Gastric motility is regulated by myoelectrical activity of the stomach[2]. The electrical activity of the stomach consists of two components: omnipresent slow waves and spike potentials[5]. Spike potentials are superimposed on the slow wave and are directly associated with the contractions of the stomach. The slow wave controls the propagation and frequency of the gastric contractions. The normal frequency of the gastric slow wave is about 3 cycles/min (cpm) in humans.

Gastric myoelectrical activity can be measured non-invasively by placing surface electrodes on the epigastric area of the abdomen. The non-invasive technique is called electrogastrography and the surface recording of the electrical activity is called the electrogastrogram or EGG[6]. Previous studies[14,15] have shown that the EGG is an accurate measurement of the frequency of the gastric slow wave and that the relative amplitude change of the EGG reflects the contractility of the stomach. The presence of gastric contractions is usually signified by an increase in amplitude of the EGG. We therefore hypothesize that an artificial neural

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network (ANN) may be trained to recognize the presence of gastric contractions within the EGG waveform.

The main attraction of ANNs is their ability to learn the functions that describe input/output mapping in a system. Neural networks have been widely employed in pattern recognition due to their great potential of high performance, flexibility, robust fault tolerance, cost-effective functionality and capability for real-time applications[7,8]. A number of successful applications of ANNs 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[9–13,25,26,30]. The problems of the EGG in clinical applications are perfect candidates for ANNs. 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. The EGG signal is imprecise. However, a large amount of data can be easily made available due to the non-invasive nature of the electrogastrographic technique. Therefore, in this study we attempt to apply ANN techniques to identify the presence of gastric contractions from the EGG signals.

MEASUREMENT OF THE ELECTROGASTROGRAM

Ten female volunteers with a mean age of 31 (range 20–39) participated in this study. All had no history of gastrointestinal diseases. After an overnight fast an upper gastrointestinal endoscopy was performed in the morning and a manometric probe was placed in the stomach and upper small intestine. Following recovery from sedation, the subjects were first taken to the Department of Radiology where the stomach was localized by ultrasonography and then to the General Clinical Research Center for overnight admission. Cutaneous electrodes were placed before supper at 4:00 pm. The subject ingested a standard test meal at 5:30 pm and nothing was given afterward. The manometric and EGG recordings were obtained in the fasting state from 1:00 am to 3:00 am.

Measurement of manometric activities:

Manometric activities of the distal stomach and the upper small bowel were recorded using an intraluminal probe (Millar Instruments Inc., Houston, Texas). The probe was about 1/8″ in diameter and was passed through the nose into the upper small bowel by endoscopic assistance. It contained six solid-state pressure transducers, located 3, 13, 23, 33, 37 and 41 centimeters from the distal end. Three ports were placed in the distal stomach and three in the upper small bowel (see *Figure 1*). The measured six channel manometric signals were displayed on a dynograph (SensorMedics, Anaheim, CA) and simultaneously

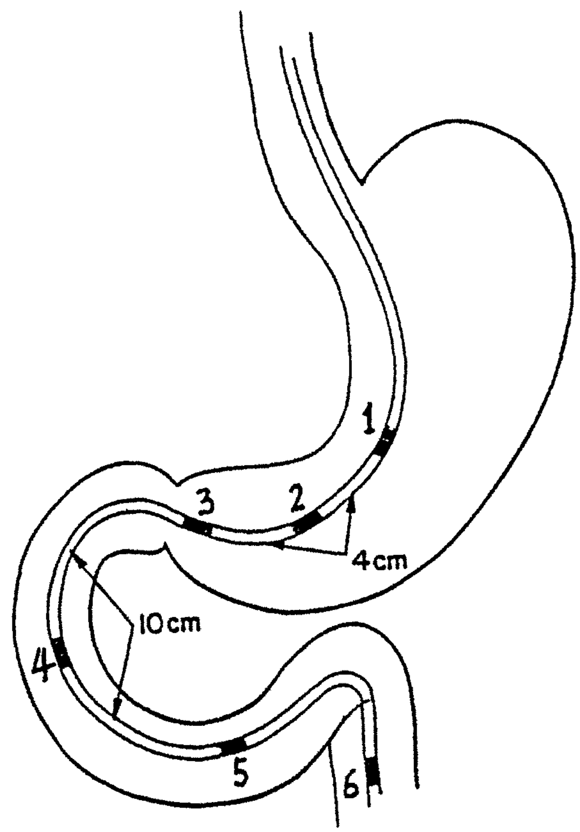

Figure 1 Position of the intraluminal manometric probe

recorded on a magentic tape (Thorn EMI 3000, England). The recording frequency range was set at 0 to 0.3 Hz.

Measurement of the electrogastrogram:

Supine ultrasonography was performed in order to mark the antral axis of the distal stomach on the abdomen. The abdominal surface of recording sites was cleaned with sandy skin prepping paste (OMNI Prep, Weaver & Co. Aurora, CA) to achieve better conduction and to reduce skin-electrode motion artefacts. Two electrodes (bio-potential skin electrode, In Vivo, Metric, CA) filled with electrode jelly were placed on the abdominal surface, one over the distal stomach and the other 6–10 cm superior near the right breast. Respiration was monitored using a Pneumotrace belt. The EGG signal was displayed on the recording chart by another dynograph chart recorder and simultaneously recorded on the same tape recorder. The low and high cut-off frequencies of the EGG recording equipment were set at 0.02 Hz (1.2 cpm) and 0.3 Hz (18 cpm), respectively (6 dB/octave). The paper speed was 0.25 mm/s. During the study, the subjects were laid in a supine position (except during eating) and remained quiet and still. The EGG data were digitized, post recording, at a sampling frequency of 2 Hz using a 12-bit A/D converter.

PRE-PROCESSING OF THE EGG

Previous studies[14,15] have shown that the EGG accurately reflects the frequency of the gastric slow wave. Therefore, spectral data points instead of raw EGG data were used as the input to the ANN. The exponential distribution method[16] introduced by Choi and Williams was applied to compute the power spectrum of the EGG data. It is a modification of the Wigner distribution and has better performance than the Wigner distribution in the suppression of cross-terms.

The exponential distribution is defined as[16]:

$$ED_x(t,\omega) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\sqrt{\frac{\sigma}{4\pi\tau^2}}\exp\left(-\frac{\sigma(\mu-t)^2}{4\tau^2}\right)\times x(\mu+\tau/2)\,x^*(\mu-\tau/2)\,e^{-j\omega\tau}d\mu d\tau \qquad (1)$$

where, $x(t)$ is a time signal, $x^*(t)$ the conjugate of the time signal, t is a time index, μ and τ are integral factors, and $\sigma(\sigma>0)$ is a scaling factor which trades off auto-term resolution for cross-term suppression or vice versa. To obtain a sharp auto-term resolution, σ should be large. On the other hand, to reduce the effects of the cross-terms, σ should be small. The exponential distribution has been proven to be effective in suppressing interferences while retaining high resolution. Cross-term suppression is achieved because cross-terms oscillate more rapidly than signal autocomponents. The ability to suppress the cross-terms comes by way of controlling the single parameter σ. In fact, as $\sigma\rightarrow\infty$ the exponential distribution becomes the Wigner distribution.

A running windowed exponential distribution (RWE) was applied in this study for the time-frequency representation of the EGG signal.

$$RWE_f(n,k) = 2\sum_{\tau=-\infty}^{\infty} W_N(\tau)e^{-j2\pi k\tau/N}\left[\sum_{\mu=-\infty}^{\infty} W_M(\mu)\sqrt{\frac{\sigma}{4\pi\tau^2}}\times\exp\left(\frac{-\sigma\mu^2}{4\tau^2}\right)x(n+\mu+\tau)\,x^*(n+\mu-\tau)\right] \qquad (2)$$

where, $x(n)$ is a digitized EGG signal, n is a time index, μ and τ are summation factors and k is the frequency index of the running windowed exponential distribution. $W_N(\tau)$ is a symmetrical window with a length of N and $W_M(\mu)$ is a rectangular window with a length of M. After obtaining the summation in the square brackets in the above equation, an N-point FFT was used to evaluate $RWE_f(n,k)$ at each time instant n.

The running windowed exponential distribution is periodic in π. To avoid aliasing in this representation, it is necessary to either sample the signal at a frequency which is at least twice the Nyquist rate or use the analytic form of the signal. In this application, the analytic form of the signal was used. Since the analytic form has energy only at positive frequencies, interference between negative and positive frequency components is avoided. The analytic signal was obtained using two FFT's: a forward FFT of a given real-valued realization, a multiplication of resulting positive harmonics by two, and negative harmonics by zero, and then an inverse FFT.

The performance of the exponential distribution method for the time-frequency analysis of the EGG has been thoroughly investigated by Lin and Chen[18]; the optimal parameters derived there are used in the present study for the time-frequency representation of the EGG. The previous study indicates that the exponential distribution method provides an accurate estimation for both frequency and amplitude of the EGG. A simulation result demonstrating its ability is presented in *Figure 2*. Panel (a) of the figure is a simulated frequency- and amplitude-modulated signal. The time-frequency representation of this signal is presented in panel (b). The time-variations of the frequency and amplitude of the signal can be clearly observed in this time-frequency representation.

BACK-PROPAGATION NEURAL NETWORKS

In comparison with other ANNs, the back-propagation neural network has the advantage of available effective training algorithm and better-understood system behaviour. It is a hierarchical design consisting of fully interconnected layers of processing nodes, with one or more hidden layers of nodes between the input and output nodes. *Figure 3* shows the back-propagation network structure used in this study. Nodes in each layer are interconnected in a feedforward fashion. The connections between different layers of nodes have associated weights which act upon the outputs of the first layer of nodes before they are passed to the next. The input nodes have no specific functions associated with them. The hidden nodes and the output nodes, however, have a transfer function. The sigmoid function was used in this study.

Training of the network was accomplished by the back-propagation algorithm[7]. The back-propagation training algorithm is an iterative gradient descent algorithm designed to minimize the mean square error between the actual output of the network and the desired output. The network was trained by initially selecting small random weights and internal thresholds between −0.3 and 0.3 and then presenting the network with training data. The weights were adjusted as follows[7]:

$$w_{ij}(t+1) = w_{ij}(t)+\eta\delta_j x_i+\alpha(w_{ij}(t)-w_{ij}(t-1))$$

where $w_{ij}(t)$ is the connection weight from a node i in one layer to a node j in another layer at time t, x_i is either an input or the output of the hidden node i, δ_j is an error term for node j, η is a learning rate factor and α is a momentum factor $(0<\alpha<1)$. If j is an output node, then

$$\delta_j = y_j(1-y_j)(d_j-y_j)$$

where d_j is the desired output of node j and y_j is the actual output. If node j is a hidden node, however, the computation of the error terms becomes

$$\delta_j = x_j(1-x_j)\sum_k \delta_k w_{jk}$$

where k is summed over all nodes in the layer above node j. Hidden node thresholds were adjusted in a similar way by assuming they are con-

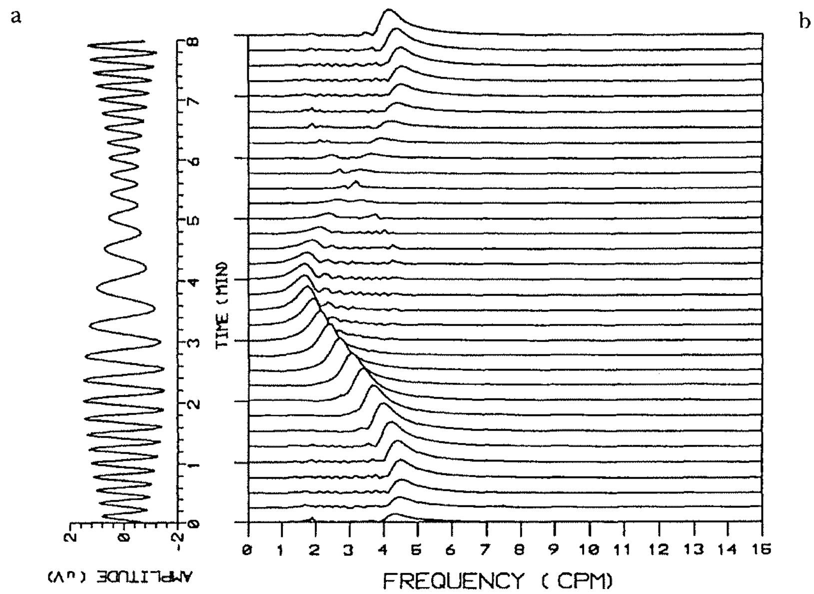

Figure 2 Time-frequency representation using the exponential distribution method. Amplitude- and frequency- modulated signal; time-frequency representation

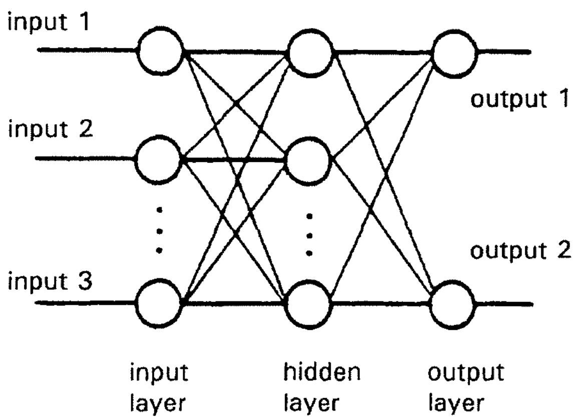

Figure 3 Structure of a three-layer back-propagation neural network

nection weights on links from auxiliary constant-valued inputs.

The effectiveness and convergence of the back-propagation algorithm depends significantly on the value of the learning rate factor η. A small learning rate factor guarantees a true gradient descent. The price of this guarantee is an increased total number of learning steps to reach a satisfactory solution. A larger learning rate factor results in a faster learning speed. However the learning may not be exact, with tendencies to overshoot, or it may never stabilize at any minimum[27]. In general, the optimal value of η is dependent on the problem to be solved and there is no universal single learning rate value for different applications. That is, the learning rate factor η should be chosen experimentally for each problem.

The use of the momentum factor is to speed up the learning process. It makes the current search direction an exponentially weighted average of past directions and helps keep the weights moving across flat portions of the performance surface after they have descended from the steep portion[28]. Similar to the learning rate factor, the optimal momentum factor should be determined experimentally.

In this study the time-frequency representation of the EGG computed by the running windowed exponential distribution method was used as the input to the network. Only 64 spectral data points were used, which covered 0 cpm to 15 cpm. Since the electrical activity of the stomach contains no information above 15 cpm, spectral data points above this frequency were discarded, which substantially simplified the structure of the network. Two output nodes of the network represent the presence of gastric contractions and gastric motor quiescence, respectively. Several parameters were optimized to achieve best performance. These included the number of hidden nodes in the hidden layer, learning rate and momentum factors.

Training and testing of ANN

The EGG recording was divided into segments. Each segment was composed of 512 time samples and was labeled as 0 or 1. The segment was labeled as 0 if no contractions were seen in the three-channel antral manometric recordings obtained simultaneously. The segment was labeled as 1 if one or more contraction was present in either of the three-channel antral manometric recordings. The power spectrum of each segment was computed by the exponential distribution method. There was an overlap of 75% between two adjacent EGG segments. The EGGS of five subjects were used for training the ANN, and for the remaining five subjects, their EGGs were used as a test set. It was a random selection. Two 20 min recording periods were extracted from each of the 10 subjects. During one 20 min period there was an absence of gastric contractions, whereas during the other 20 min period there were intermittent or continuous gastric contractions.

Performance of the neural network

The performance of the neural network was evaluated based on the accuracy of identification. The accuracy (or recall) was defined as the number of correct positive diagnoses by the network divided by the total number of positive diagnoses by the gold standard. The accuracy for the identification of gastric contractions was defined as the number of EGG segments positively identified by the network, divided by the number of EGG segments with actual presence of gastric contractions assessed from the manometric recording. Similarly the accuracy for the identification of gastric motor quiescence was defined as the number of EGG segments from which no gastric contractions were identified by the network, divided by the number of EGG segments with actual absence of gastric contractions. The overall accuracy was defined as the mean of the accuracy for the identification of gastric contractions and that for the identification of gastric motor quiescence.

RESULTS

The electrogastrogram

Regular 3 cpm slow waves were seen in the EGG. The EGG exhibited a larger amplitude and more variation in frequency whilst gastric contractions were occurring than during gastric motor quiescence. Typical EGG signals are presented in *Figure 4*. The (a) panels show the EGG and one of the three-channel antral manometric recordings during motor quiescence and the (b) panels, the EGG whilst gastric contractions were occurring.

Time-frequency representation of the EGG

The time-frequency representation of the typical EGG signal is shown in *Figure 5*. *Figure 5a* shows the time-frequency representation of a portion (20 min) of the EGG during motor quiescence and *Figure 5b* illustrates the EGG during gastric contractions. It is seen that the EGG during gas-

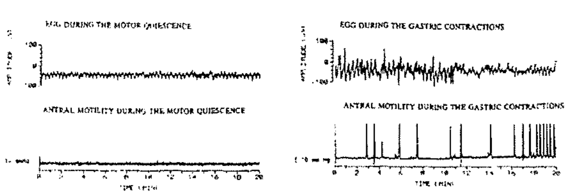

Figure 4 EGG and simultaneous gastric motility recordings. (a) measurements during gastric motor quiescence; (b) measurements during gastric contractions

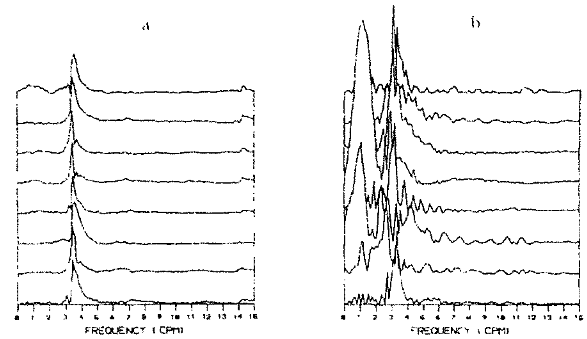

Figure 5 Time-frequency representations of the EGG during motor quiescence (a) and during gastric contractions (b). Higher power and more low frequency components are observed in the EGG during gastric contractions

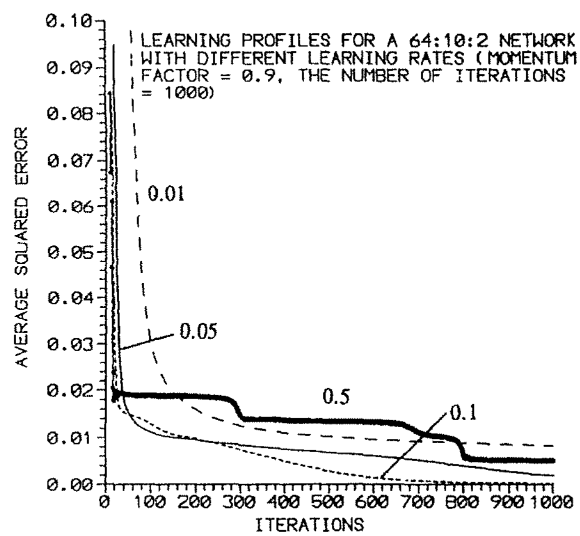

Figure 6 Effects of learning rate on network performance

tric contractions has a higher power at 3 cpm and more low frequency components between 0 and 3 cpm.

Neural networks

Different learning rates were investigated in the range of 0.01 to 0.5. *Figure 6* and *Table 1* show the effect of the learning rate on the performance (average squared error) of the network with a structure of 64:10:2 (nodes of input:hidden: output). The best performance was observed

Table 1 Effects of the learning rate on the performance of a 64:10:2 network. (momentum factor = 0.9, number of iterations = 1000)

learning rate	ave. sq. error	accuracy (train)	accuracy (test)
0.01	0.008	100%	89%
0.05	0.002	100%	92%
0.1	0.0002	100%	92%
0.5	0.005	100%	50%

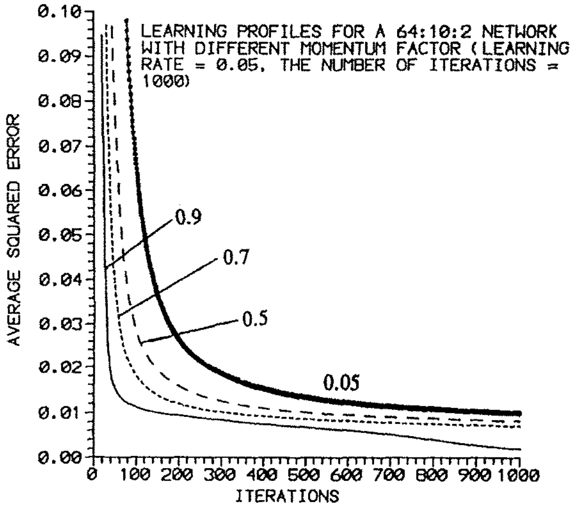

Figure 7 Effects of momentum factor on network performance

Table 2 Effects of the momentum factor on the performance of a 64:10:2 network. (learning rate = 0.05, number of iterations = 1000)

momentum factor	ave. sq. error	accuracy (train)	accuracy (test)
0.05	0.01	100%	89%
0.5	0.008	100%	92%
0.7	0.007	100%	92%
0.9	0.002	100%	92%

when the rate was chosen between 0.05 and 0.1, with which an overall accuracy of 100% was obtained for the training set and 92% for the testing set. The effect of the momentum factor on the performance of the same network is illustrated in *Figure 7* and *Table 2*. The optimal momentum factor was found to be 0.9 for a fixed number of 1000 iterations. Finally, the effect of the number of the hidden nodes is presented in *Table 3*. With a fixed number of iterations, ten hidden nodes resulted in better performance than five hidden nodes, whereas no further improvement was observed with the number of hidden nodes larger than 10. With the structure of 64:10:2 and the optimized values of the learning rate (0.05) and momentum factor (0.9), the network identified gastric quiescence with an accuracy of 90% and gastric contractions with an accuracy of 94% from the EGGs.

Table 3 Effects of the number of hidden nodes on the performance of the network (testing results). (learning rate = 0.05, momentum factor = 0.9, number of iterations = 1000)

hidden nodes	accuracy (quiescence)	accuracy (contractions)
5	84%	91%
10	90%	94%
20	90%	94%
30	90%	94%

DISCUSSION AND CONCLUSIONS

This paper shows that the patterns (contractions or quiescence) of gastric motility may be identified from non-invasive EGG recording using the back-propagation neural network. It is known that gastric motility plays an important role in the digestive process of the stomach. The absence of gastric contractions in the fasting state (or absence of the MMC) is often associated with the clinical state referred to as gastrointestinal pseudo-obstruction. Whereas, the absence of gastric contractions in the fed state results in a delayed gastric emptying called gastroparesis. Patients with severe gastroparesis cannot tolerate solid meals and have to limit nutrition intake to liquid calories. Currently the measurement of gastric motility is performed by intubating the upper gastrointestinal tract with a manometric probe. This is not only invasive but biased since the intubation of the probe may disturb the normal on-going activity of the stomach. Using the method proposed in this paper, the patterns of gastric motility can be non-invasively identified from the EGG. Since the measurement of the EGG does not at all disturb the on-going activity of the stomach, our method may not only provide an alternative to the current invasive method but also be more physiologically reliable than the current invasive method. If absence of gastric contractions is reported from the EGG by the ANN, a recommendation can be made to treat the patient using prokinetic agents known to stimulate gastric motility.

The time-frequency representation of the EGG was used as the input to the neural network. This is because the raw EGG contains interferences from other parts of the human body[21], such as ECG, respiration artefacts and small intestinal electrical activity (10–12 cpm). These interferences are usually separated from the gastric myoelectrical activity in the frequency domain. Several methods for the time-frequency representation of the EGG have reported in the literature. These include the short-time fast Fourier transform (STFFT)[22] and adaptive spectral analysis[23,24]. The application of the exponential distribution method was introduced recently[29]. The exponential distribution method is linear in the estimation of both the frequency and amplitude information.

The success of the neural networks in a specific application involves the optimization of the network structure and parameters. Numerous experiments were conducted in this study to obtain a better network. One hidden layer was used based on several previous studies[20] which showed that one hidden layer resulted in the same performance as two or more hidden layers. Conflicting results were reported in the literature on the number of hidden nodes[27]. The selection of the number of hidden nodes in this study was based on experiments which showed that 10 hidden nodes were as effective as 40 nodes for a fixed iteration of 1000. Other experimental results showing the effects of the learning rate and the momentum factor were consistent with previous findings by others[8].

In conclusion, this paper presents a non-invasive method for the identification of gastric contractions from the surface electrogastrogram using the back-propagation neural network.

ACKNOWLEDGEMENT

Acknowledgement is made to the Whitaker Foundation and the Thomas F. and Kate Miller Jeffress Memorial Trust for the support of this research.

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