Communications

Noninvasive Feature-Based Detection of Delayed Gastric Emptying in Humans Using Neural Networks

J. D. Z. Chen*, Zhiyue Lin, and Richard W. McCallum

Abstract—**Radioscintigraphy is currently the gold standard for gastric emptying test which involves radiation exposure and is considerably expensive. We present a feature-based detection approach using neural networks for the noninvasive diagnosis of delayed gastric emptying from the cutaneous electrogastrogram (EGG). Simultaneous recordings of the EGG and scintigraphic gastric emptying test were made in 152 patients with symptoms suggestive of delayed gastric emptying. Spectral analyses were performed to derive EGG parameters which were used as the input of the neural network. The result of scintigraphic gastric emptying was used as the gold standard for the training and testing of the neural network. A correct classification of 85% (a specificity of 89% and a sensitivity of 82%) was achieved using the proposed method.**

Index Terms—**Artificial neural networks , spectral analysis, electrogastrogram, gastric emptying.**

I. Introduction

Radioscintigraphy is currently the commonly used method for the gastric emptying test to assess the digestive process of the stomach. In this method, a patient is instructed to digest a meal with radioactive materials and then to stay under a gamma camera for acquiring abdominal images for several hours. The application of this technique is radioactive and considerably expensive, and usually limited to very sick patients. Therefore, a noninvasive and low-cost method for the detection of delayed gastric emptying is needed, which may then be applied to patients with mild to moderate functional disorders of the gut (about 20% of general population).

It is known that gastric myoelectrical activity is the most fundamental activity of the stomach and it modulates gastric motor activity. The frequency and propagation of gastric contractions are controlled by the gastric slow wave. The normal frequency of the gastric slow wave is in the 2–4 cycles per minute (cpm) range in humans. Abnormalities in the frequency of the gastric slow wave have been associated with gastric motor disorders and gastrointestinal symptoms. These include abnormally low frequencies termed bradygastria (0.5–2 cpm) and abnormally high frequencies termed tachygastria (4–9 cpm). The electrogastrogram (EGG) is a cutaneous recording of the gastric slow wave from abdominal surface electrodes. The EGG is attractive because it is noninvasive and does not disturb ongoing activity of the stomach. Numerous studies have shown that the EGG is an accurate measure of the gastric slow wave [1]–[3]. In a previous study, significant differences were found in a number of EGG parameters between the patients with actual delayed gastric emptying and those with normal gastric emptying [4]. The aim of this study was to differentiate patients with normal and delayed emptying of the stomach from the EGG using the artificial neural network (ANN).

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II. Methods

A. Measurements of the EGG and Scintigraphic Gastric Emptying

The EGG data used in this study were obtained from 152 patients (110 women, 42 men; mean age: 43.3 and range: 17–74 years) with suspected gastric motility disorders who underwent clinical tests for gastric emptying from March of 1992 to July of 1996 at University of Virginia Health Sciences Center, Charlottesville, VA. A 30-min baseline EGG recording was made in a supine position before the ingestion of a standard test meal in each patient. Then, the patient sat up and consumed a standard test meal within 10 min. After eating, the patient resumed the supine position and simultaneous recordings of the EGG and scintigraphic gastric emptying were made continuously for 2 h. The EGG signal was amplified using a portable EGG recorder with low and high cutoff frequencies of 1 and 18 cpm, respectively. On-line digitization with a sampling frequency of 1 Hz was performed and digitized samples were stored on the recorder. All recordings were made in a quiet room and the patient was asked not to talk and to remain as still as possible during the recording to avoid motion artifacts. The techniques for recording the EGG and gastric emptying were previously described [4]. The interpretation of gastric emptying results was made by the nuclear medicine physicians.

B. Feature Extraction

Previous studies have shown that spectral parameters of the EGG provide useful information regarding gastrointestinal motility and symptoms [5]. Whereas, the waveform of the EGG is unpredictable and does not provide reliable information. Therefore, all EGG data were subjected to computerized spectral analysis using the programs previously developed in our laboratory [6]. The following EGG parameters were extracted from the spectral domain of the EGG data in each patient and were used as the input to the neural network.

1) EGG Dominant Frequency and Power: The frequency at which the EGG power spectrum has a peak power in the range of 0.5 to 9.0 cpm was defined as the EGG dominant frequency. The power at the corresponding dominant frequency was defined as EGG dominant power. Decibel (dB) units were used to represent the power of the EGG. The smoothed power spectral analysis method [6] was used to compute an averaged power spectrum of the EGG during each recording, including the 30-min fasting EGG (A) and 120-min postprandial EGG (B). These two parameters represent the mean frequency and amplitude of the gastric slow wave.

2) Post Prandial Increase of EGG Dominant Power: The postprandial increase of EGG dominant power was defined as the difference between the EGG dominant powers after and before the test meal, i.e., the EGG dominant power during the recording period B minus that during the recording period A. The reason for the use of the relative power of the EGG as a feature is that the absolute value of the EGG power is associated with several factors unrelated to gastric motility or emptying, such as the thickness of the abdominal wall and the placement of the electrodes. The relative change of EGG power is related to the regularity and amplitude of the gastric slow wave, and has been reported to be associated with gastric contractility.

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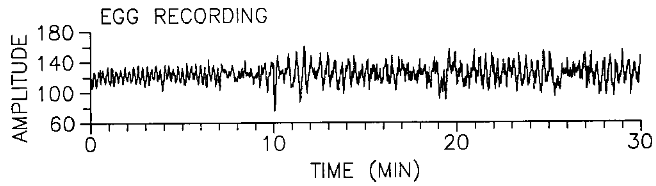
3) Percentages of Normal Gastric Slow Waves and Gastric Dysrhythmias: The percentage of the normal gastric slow wave is a quantitative assessment of the regularity of the gastric slow wave measured from the EGG. It was defined as the percentage of time during which normal 2–4 cpm slow waves were observed in the EGG. It was calculated using the running power spectral analysis method [6]. In this method, each EGG recording was divided into blocks of 2 min without overlapping. The power spectrum of each 2-min EGG data was calculated and examined to see if the peak power was within the range of 2 to 4 cpm. The 2-min EGG was called normal if the dominant power was within the 2–4 cpm range. Otherwise, it was called gastric dysrhythmia.

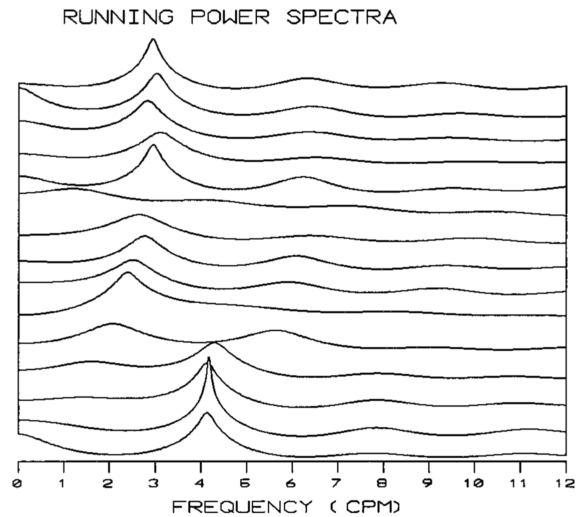
Gastric dysrhythmia includes tachygastria, bradygastria, and arrhythmia. The correlation between bradygastria and gastric motility is not completely understood. Whereas, tachygastria has been shown to be associated with gastric hypomotility [5]. Therefore, the percentage of tachygastria was calculated and used as a feature to be inputted into the neural network. It was defined as the percentage of time during which 4–9 cpm slow waves were dominant in the EGG recording. It was computed in the same way as for the calculation of the percentage of the normal gastric slow wave.

Fig. 1 presents an example of a 30-min EGG recording and it's running power spectra. Each curve from bottom to top in this figure [Fig. 1(b)] is the power spectrum of the consecutive 2-min EGG data. It is seen that nine power spectra have their peak powers in the range of 2 to 4 cpm and, therefore, the percentage of the normal slow wave is 60% $(9/15)$. It is also seen that there are four spectra that have peak powers in the range of 4 to 9 cpm and, thus, the percentage of tachygastria is 27% $(4/15)$.

In order to preclude the possibility of some features dominating the classification process, the value of each parameter was normalized to the range of zero to one. Experiments were performed using all or part of the above parameters as the input to the ANN to derive an optimal performance.



(a)



(b)

Fig. 1. (a) An example of a 30-min EGG recording and (b) its running power spectra showing the calculation of the percentages of normal 2–4 cpm waves and tachygastria (4–9 cpm).

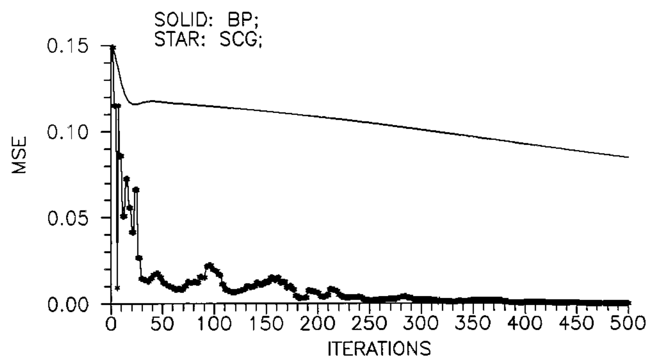


Fig. 2. The mean squared error (MSE) for the backpropagation algorithm and SCG algorithm in training a three-layer network.

C. Structure of the Neural Network and Learning Algorithm

The multilayer feed-forward neural network was chosen as a classifier for the diagnosis of delayed gastric emptying from the EGG due to its success in various pattern classifications [7], [8]. Previous studies have shown that for the classification problem where the output node with the greatest activitation would determine the category of the input pattern, one hidden layer will most likely be sufficient [8]. Thus, a three-layer feed-forward network was designed in this study. The number of hidden nodes was determined experimentally. The output of the network had two nodes, standing for delayed gastric emptying and normal gastric emptying, respectively. The number of the input nodes was determined by the number of EGG parameters. A number of experiments were conducted to optimize the performance of the network using different numbers of the EGG parameters ranging from two to all of the parameters.

The optimal set of network weights for a particular problem is obtained through a learning process. Several adaptive learning algorithms for the multilayer neural network have been proposed in the literature. It has been shown that the performance of a scaled conjugate gradient algorithm (SCG) is benchmarked against that of the standard backpropagation algorithm (BP) [9]. The BP refers to the algorithm using the generalized delta rule and momentum. The SCG algorithm is based on the conjugate gradient method which chooses the search direction and step size by using information from the second order Taylor expansion of the error function. It is fully automated and does not contain crucial user-dependent parameters such as learning rate and momentum constant in the BP and, therefore, a time-consuming long search is avoided. Experiments showed that the SCG algorithm is considerably faster than the BP. Therefore, the SCG algorithm was used as supervised learning algorithm during training.

D. Evaluation of the Performance

The performance of the developed neural network was evaluated by computing the percentages of correct classification (CC), sensitivity (SE), and specificity (SP) by using

$$\mathrm{CC} = 100 \times (\mathrm{TP} + \mathrm{TN})/N$$
$$\mathrm{SE} = 100 \times \mathrm{TP}/(\mathrm{TP} + \mathrm{FN})$$
$$\mathrm{SP} = 100 \times \mathrm{TN}/(\mathrm{TN} + \mathrm{FP})$$

TABLE I
TESTING RESULTS OF THE ANN

No. Of nodes Input-hidden-output	Accuracy for testing data		
	CC(%)	SE(%)	SP(%)
5-5-2	80	74	87
5-4-2	80	74	87
5-3-2	85	82	89
5-2-2	80	74	87
4-3-2	80	74	87
3-3-2	72	74	71

CC(%): the percentage of correct classification; SE: sensitivity = true positive divided by all positive diagnosis; SP: specificity = true negative divided by all negative diagnosis.

where, N was the total number of the patients, TP was the true positives, TN was the true negatives, FN was the number of false negatives, and FP was the number of false positives [7]. The training was terminated when the maximum of iterations (2000) was encountered or a preset error threshold (0.1) was attained.

III. RESULTS

The EGG data obtained from the 152 patients were divided into two groups based on the results of the scintigraphic gastric emptying test: 76 patients with delayed gastric emptying and 76 patients with normal gastric emptying. The training set was composed of EGG data in 50% of the patients from each of the groups, and the remaining data was used as the testing set. The statistical analysis of the EGG parameters between the two groups of the patients revealed that the patients with delayed gastric emptying had a lower percentage of regular 2–4 cpm slow waves in both fasting (77.1 ± 2.6% versus 88.7 ± 1.3%, $p < 0.001$) and fed (77.8 ± 2.2% versus 90.0 ± 1.0%, $p < 0.001$) states. A significant higher level of tachygastria was also observed in the fed state in patients with delayed gastric emptying (13.9 ± 1.8% versus 4.1 ± 0.6%, $p < 0.001$). Both groups of the patients showed a postprandial increase in EGG dominant power. This increase was however significantly lower in patients with delayed gastric emptying than in patients with normal gastric emptying (1.2 ± 0.6 dB versus 4.6 ± 0.5 dB, $p < 0.001$). No significant differences were observed in the dominant frequency of the EGG between the two groups in the fasting (3.08 ± 0.10 cpm versus 2.94 ± 0.03 cpm, $p > 0.05$) and fed (3.20 ± 0.10 cpm versus 3.03 ± 0.03 cpm, $p > 0.05$) states.

The convergence speed of the SCG algorithm was compared with the BP. Fig. 2 presents the mean squared error (MSE) [7] as a function of the number of iterations for these two algorithms in training the proposed three layer network with three nodes in the hidden layer. It can be seen clearly that the convergence rate of the SCG is much faster than that of the BP.

Table I presents the test results of the network with different nodes in the input layer and in the hidden layer. Since using three to five parameters as the input to the network provided better results than using two or more than five parameters, Table I only shows the results of at least three parameters used in this study. The three parameters used were the postprandial increase of the EGG dominant power, the percentages of normal 2–4 cpm slow waves in the fasting state and fed state. The five parameters included were the dominant frequency in the fasting state, the dominant frequency in the fed state, the postprandial increase of the EGG dominant power, the percentage of normal 2–4 cpm slow waves in the fed state, and the percentage of tachygastria in the fed state. These five parameters were determined based on a series of experiments using different combination of all EGG parameters. It can be seen that the best performance was achieved when these five parameters were used as the input and the hidden layer had three nodes. In this case, the accuracy of the correct diagnosis was 85% with a sensitivity of 82% and a specificity of 89%. It can also be seen that three nodes are the optimal number for the hidden layer and that exclusion of any one or two of the five input parameters would deteriorate the performance of the classification.

IV. DISCUSSION

The reasons for choosing the neural network approach was as follows: 1) although no exact rules could be written to define gastric emptying based on the EGG some differences in EGG parameters do exist between the patients with normal and delayed gastric emptying; 2) the measurement of the EGG is noninvasive and well accepted by patients and physicians. Therefore, ample data can be made available without any difficulty for the training and testing of the neural network; 3) The application of the ANN for the classification of other medical data has been reported in numerous previous studies [10]–[13]. In our laboratory, the ANN has been successfully applied to identify motion artifacts in the EGG recording [14], to detect gastric contractions from the EGG [15], and to classify the EGG into four categories of bradygastria, normal, tachygastria, and arrhythmia [16]. High accuracies were achieved in all of these previous applications.

The structure of the neural network and the parameters of the EGG in this study were determined based on the literature and experiment. One hidden layer was used based on several previous studies [17] 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 [18]. The selection of the number of hidden nodes in this study was purely based on the experiments. The selection of the EGG parameters was based on the statistical analysis of the EGG parameters between the patients with normal and delayed gastric emptying. Among the five parameters used as the input, statistical differences existed between the two groups of the patients in the percentages of the regular 2–4 cpm wave, the percentage of tachygastria, and the postprandial increase in EGG dominant power.

One may have noted that the accuracy of the method proposed in this paper for the prediction of gastric emptying is moderate and not very high. This is associated with the characteristic of gastric emptying and its association with gastric myoelectrical activity. Although the gastric motor function is usually the major player in gastric emptying, any abnormalities in the pylorus, such as pyloric stenosis, or in the small bowel, such as intestinal pseudoobstruction could lead to delayed emptying of the stomach. It is well known that gastric myoelectrical activity is only associated with gastric motor function and has nothing to do with the pylorus and the small intestine. It is, therefore, expected that the accuracy of the proposed method would not be very high. Particularly, the sensitivity is lower and the specificity is higher. This is because normal gastric myoelectrical activity cannot always guarantee normal gastric emptying and abnormal gastric myoelectrical activity usually results in delayed gastric emptying.

In summary, the proposed ANN method provides an alternative for the prediction of gastric emptying. In comparison with the conventional scintigraphic method of gastric emptying, the proposed method is noninvasive, well received among physicians and patients, and more cost effective.

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A New Video-Synchronized Multichannel Biomedical Data Acquisition System

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***Abstract*—This data acquisition system records video frames onto a video tape, and simultaneously acquires biomedical data along with video time codes onto a computer hard disk to achieve a 30-min video-synchronized data recording with a summed data rate of 2.16 Mbit/s. A time-code-bridge-file created during acquisition matches each video frame-start with the corresponding index number of the acquired data. The mean synchronization accuracy of the system is 0.22 ms.**

***Index Terms*—Data acquisition, multichannel, time code, video frame-start, video synchronization.**

I. Introduction

Video-synchronized data acquisition is finding more applications in biomedical engineering research. Some of these applications require a video-synchronized data-acquisition system with multidata

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