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Technical note

Application of combined genetic algorithms with cascade correlation to diagnosis of delayed gastric emptying from electrogastrograms

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Abstract

The current standard method (radioscintigraphy) for the diagnosis of delayed gastric emptying (GE) of a solid meal involves radiation exposure and considerable expense. Based on combining genetic algorithms with the cascade correlation learning architecture, a neural network approach is proposed for the diagnosis of delayed GE from electrogastrograms (EGGs). EGGs were measured by placing surface electrodes on the abdominal skin over the stomach in 152 patients with suspected gastric motility disorders for 30 min in the fasting state and for 2 h after a standard test meal. The GE rate of the stomach was simultaneously monitored after the meal using radioscintigraphy. Five spectral parameters of EGG data in each patient were used as the inputs to a classifier. The classifier was designed by using genetic algorithms in conjunction with the cascade correlation learning architecture. The main advantage of this technique over the back-propagation (BP) for supervised learning is that it can automatically develop the architecture of neural networks to give a suitable network size for a specific problem. The resulted neural network with three hidden units exhibits 83% correct classification for the EGG data, and has comparable performance with the BP network. This study demonstrates the potential of the neural network approach based on combined genetic algorithms with cascade correlation for diagnosis of gastric emptying from the EGG.

Keywords: Artificial neural networks; Spectral analysis; Electrogastrogram; Gastric emptying; Genetic algorithm

1. Introduction

Gastric emptying is a commonly used test for the assessment of the digestive process of the stomach. The methodology for assessment of gastric emptying rate has been established in different laboratories. A patient is said to have a delayed gastric emptying if more than 70% of ingested solid meal remains in the stomach 2 h after eating the meal. The currently standard gastric emptying test, known as radioscintigraphy, is performed by asking the patient to eat a radio-active solid test meal and then to stay under a gamma camera for acquiring abdominal images for 2 h [1]. The application of this technique is not only invasive but also expensive. Therefore, low-cost methods for non-invasive diagnosis of delayed gastric emptying are needed.

It is desirable to automatically diagnose delayed gastric emptying from the electrogastrogram (EGG) due to its non-invasive nature and lack of interference with the ongoing activity of the stomach. The EGG is a cutaneous recording of gastric myoelectrical activity obtained by placing surface electrodes on the abdominal skin over the stomach. It is known that the frequency and propagation of gastric contractions are determined by gastric slow waves. The normal frequency of the gastric slow wave is in the 2–4 cycles/min (cpm) range. As gastric motility is regulated by gastric myoelectrical activity, abnormalities in gastric myoelectrical activity may lead to gastric motor abnormalities and delayed gastric emptying [1–3]. Recently, the application of the multilayer feedforward back-propagation neural network (BPNN) for automated diagnosis of delayed gastric emptying from the EGG has been reported with some success [4],

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but one major problem is the difficulty in selection of the adequate neural network structure (number of layers, number of neurons per layer and connectivity) for a given task.

In this paper a constructive algorithm for artificial neural networks, the genetic cascade correlation algorithm (GCCA) [5], is presented for the non-invasive diagnosis of delayed gastric emptying from cutaneous EGGs. In this method, the genetic algorithm [6] is first applied over all the possible sets of weights in the cascade correlation learning architecture [7] and then the gradient descent technique is applied to converge to a solution. Although the diagnosis result for this approach is comparable with that obtained by the BPNN, the advantage of the GCCA over the BP algorithm is that it can automatically develop the architecture of neural networks to give a suitable network size for a specific problem.

2. Methods

2.1. Measurements of EGGs and gastric emptying

The EGG data were obtained from 152 patients with suspected gastric motility disorders who underwent clinical tests for gastric emptying. 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 over a period of 10 min. After eating, the patient resumed a supine position under a gamma camera and simultaneous recordings of the EGG and emptying rate of the stomach were made continuously for 2 h. Abdominal images were acquired every 15 min. 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 (Synectics Medical, Inc., Irving, TX, USA). 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 [1]. The interpretation of gastric emptying results was made by the nuclear medicine physicians.

2.2. Feature extraction

Previous studies [1,8] have shown that spectral parameters of the EGG provide useful information regarding gastrointestinal motility and symptoms, whereas the waveform of the EGG is unpredictable and does not provide reliable information. Therefore, all EGG data were subjected to computerized spectral and running spectral analysis using programs previously developed [8]. The following EGG parameters extracted from the spectral domain of EGG data in each patient were used as the inputs to the neural network.

2.2.1. EGG dominant frequency and power

The frequency at which the EGG power spectrum has a peak power in the range of 0.5–9.0 cpm was defined as the EGG dominant frequency. The power at the dominant frequency in the power spectrum of the EGG was defined as the EGG dominant power. Decibel (dB) units were used to present the power of the EGG. An example for the computation of the EGG dominant frequency and power is shown in Fig. 1. Fig. 1(A) presents a 30-min EGG recording in the fasting state obtained in one patient. The power spectrum of this 30-min EGG recording is illustrated in Fig. 1(B). Based on this spectrum, the dominant frequency of the 30-min EGG shown in Fig. 1(A) is 4.67 cpm and the dominant power is 30.4 dB. The smoothed power spectral analysis method [8] was used to produce an averaged power spectrum of the EGG during each recording period including the 30-min fasting EGG (EGG1) and 120-min postprandial EGG (EGG2).

2.2.2. Postprandial EGG dominant power change

The postprandial EGG power change 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 “EGG2” minus that during the recording period “EGG1”. 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 skin conductance, the thickness of the abdominal wall and the placement of the electrodes. However, the relative power of the EGG is associated with the regularity of the gastric slow wave and gastric contractility [8].

2.2.3. Percentages of normal slow waves and tachygastria

The percentage of normal slow waves is a quantitative assessment of the regularity of gastric slow waves 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 spectral analysis method [8]. 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 2–4 cpm. The 2-min EGG was called normal if the dominant power was within the 2–4 cpm range. Otherwise it may be called dysrhythmia. Fig. 1 presents an example of a 30-min EGG recording (A) and its running power spectra (C) derived from the adaptive spectral analysis method. Each curve (from bottom to top)

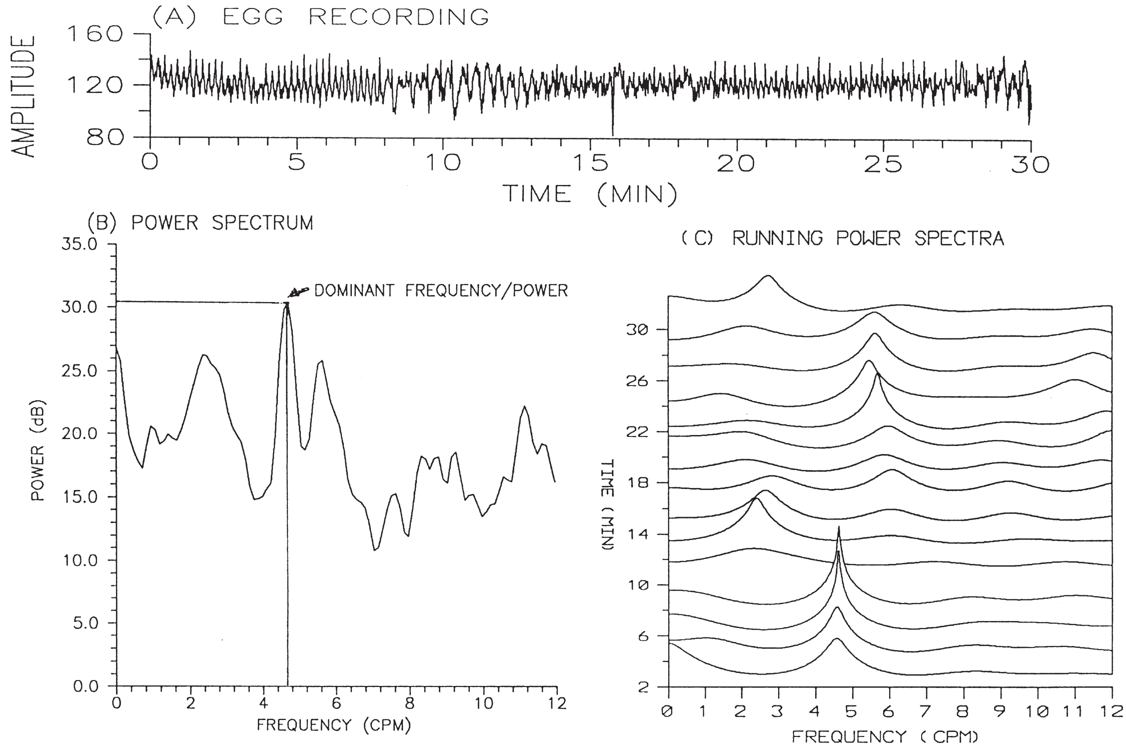

Fig. 1. (A) An example of a 30-min EGG recording, (B) its power spectrum, and (C) running power spectra showing the calculation of the dominant frequency/power of the EGG, the percentages of normal 2–4 cpm gastric slow waves and tachygastria (4–9 cpm).

in this figure is the power spectrum of 2-min EGG data. It is seen that there is 5 out of 15 running power spectra having peaks in the range of 2–4 cpm and, therefore the percentage of the normal slow waves is 33% (5/15).

Gastric dysrhythmia includes tachygastria (4–9 cpm) and bradygastria (0.5–2 cpm). It has been shown that the correlation between bradygastria and gastric motility is not clear and that tachygastria is associated with gastric hypomotility [8]. Therefore, the percentage of tachygastria was calculated and used as a feature of the EGG. It was defined as the percentage of time during which 4–9 cpm slow waves were observed in the EGG recording. It was calculated in a similar way for the calculation of the percentage of normal gastric slow waves as show in Fig. 1. For this example, the percentage of tachygastria is 67% (10/15).

In order to preclude the possibility of some features dominating the classification process, the value of each feature was normalized between 0 to 1.

2.3. Genetic cascade correlation algorithm

The genetic cascade correlation algorithm (GCCA) [5] is an improved version of cascade correlation learning architectures [7], in which the genetic algorithm [6] is used in conjunction with the cascade correlation learning architecture. The basic idea of this improved algorithm is first to apply the genetic algorithm over all the possible sets of weights in the cascade correlation learning architecture and then to apply the gradient descent technique (for instance, Quickprop [9]) to converge on a solution. This approach can automatically grow the architecture of the neural network to give a suitable network size for a specific problem. An overall outline of the GCCA is as follows [5]:

Step 1. Initialize the network: Set up initial cascade-correlation architecture.

Step 2. Train output layer: The output layer weights are optimized by the genetic algorithm using populations of chromosomes on which the weights of the output layer are encoded. If the error could not be reduced significantly in a reasonable number of generations or the timeout (i.e. the maximum number of generations allowed) has been reached, then use Quickprop to adjust weights of output layer. If the learning is complete, then stop; else if error could not be reduced significantly in a patience number of consecutive epochs or the timeout has been reached, then go to the next step.

Step 3. Initialize candidate units: Create and initialize a random population sized to fit the problem. Each string in the population represents weights linking a candidate unit to input units, all pre-existing hidden units and bias unit.

Step 4. Train candidate units: Perform genetic search in weight space of candidate unit and use Quickprop to adjust weights of candidate unit so as to maximize

the correlation between activation of the candidate unit and the error of the network. If the correlation could not be improved significantly in a patience number of consecutive epochs or the timeout has been reached, then go to the next step.
Step 5. Install a new hidden unit: Select the candidate unit with the highest correlation value and install it in the network as a new hidden unit. Now freeze its incoming weights and initialize the newly established outgoing weights. Go to step 2.

In essence, experiments have demonstrated that the network obtained with this technique is of small size and is superior to the standard BPNN classifier [5].

3. Results

Based on the result of established gastric emptying tests (radioscintigraphy), the EGG data obtained from 152 patients were predefined as two classes: 76 patients with delayed gastric emptying and 76 patients with normal gastric emptying. The training set contained 38 patients with delayed gastric emptying and 38 with normal gastric emptying randomly selected from 152 patients. The remaining 76 patents were used as testing set which also contained 38 patients with delayed gastric emptying and 38 with normal gastric emptying.

For the GCCA, both output and hidden layer weights, which were initially randomized in the range of -1 to 1, were encoded as binary strings and concatenated to form the chromosomes to be used by the genetic algorithm. Each of chromosomes represented a different set of weights. We used a population of 50 chromosomes with the crossover probability of 0.6 and the mutation probability of 0.01, and allowed the population 20 generations for convergence. Quickprop was applied for a maximum number of 1000 iterations or a preset error threshold (0.001) was achieved or a user-defined limit of hidden neurons (10) was reached.

The network was constructed step by step as outlined in the algorithm. Each hidden-unit-added processing is illustrated in Fig. 2. The initialization of the network is shown in Fig. 2(a) where we have five inputs and one output (steps 1–2 in the GCCA). The number of inputs in the network was five that was determined by the dimension of input vectors for EGG data in each patients, i.e. five spectral parameters of the EGG data in each patient. The five parameters used were the dominant frequency in the fasting state, the dominant frequency in the fed state, the postprandial EGG power change, the percentage of normal 2–4 cpm slow waves in the fed state and the percentage of tachygastria in the fed state. One output was used to present the results: delayed gastric emptying or normal gastric emptying. Fig. 2(b) shows the network after one hidden unit is added (steps 2–5 in the GCCA). As the GCCA continues, the network with two hidden units is shown in Fig. 2(c). The architecture of the developed neural network is shown in Fig. 3 where the three solid circles represent the hidden units with the order of installation from bottom to up.

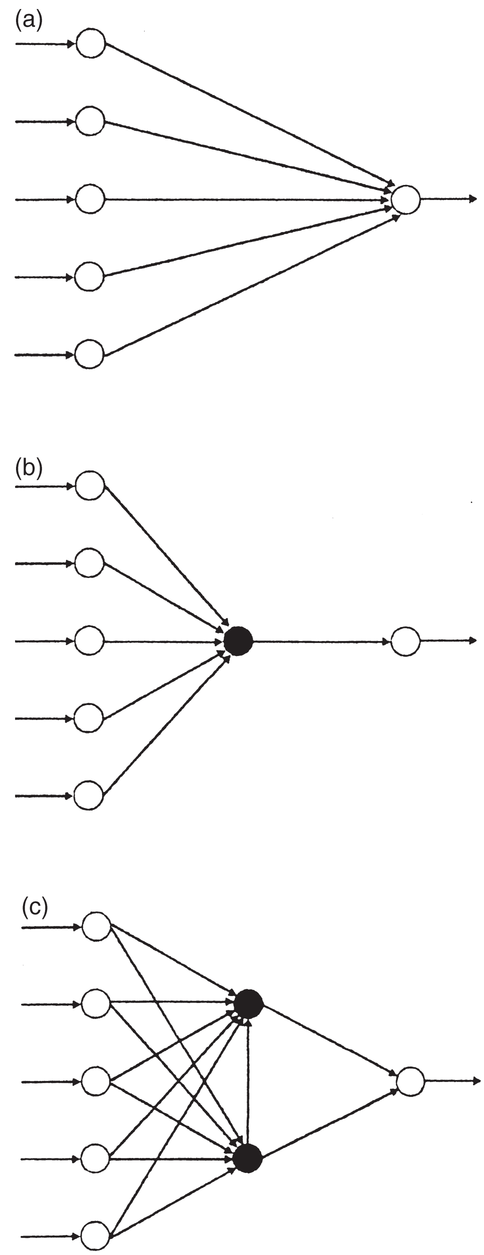

Fig. 2. Illustrations of the network evolution at different stages when the hidden unit is added. (a) Network initialization with no hidden unit, (b) the network with one hidden unit, and (c) the network with two hidden units.

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

$$CC=100*(TP+TN)/N$$

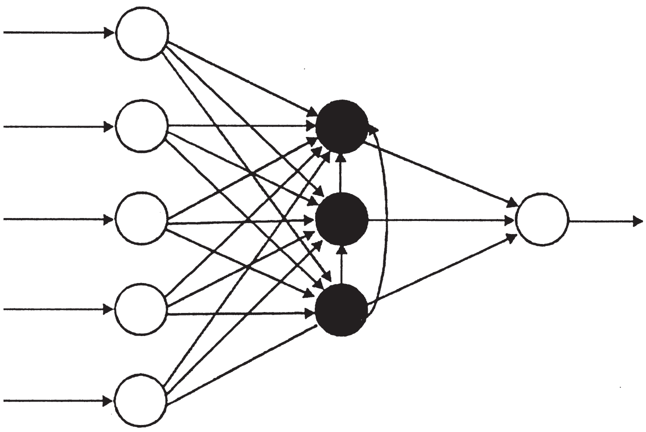

Fig. 3. The architecture of the developed neural network with 3 hidden units (solid circles).

$$SE=100*TP/(TP+FN)$$

$$SP=100*TN/(TN+FP)$$

where N was the total number of patients studied, TP was the number of true positives, TN was the number of true negatives, FN was the number of false negatives, and FP was the number of false positives [10].

Table 1 shows the experimental results for test set using networks with 2, 3, and 7 of hidden units developed by the GCCA. It can be seen from this table that the network with 3 hidden units seems to be a good choice for this specific application, which exhibits a correct diagnosis of 83% cases with a sensitivity of 84% and a specificity of 82%. The result achieved with 3 hidden units is comparable with that previously obtained by the BPNN [4]. However, the GCCA provides an automatic model selection procedure without guessing the size and connectivity pattern of the network in advance for a given task.

4. Discussion and conclusions

The neural network is a practical and powerful means used in various domains. For the EGG signal processing, a number of successful applications have been reported, including separation of the gastric signal from noisy EGGs [11], identification of gastric contractions [12], and classification of normal and abnormal EGGs [13] etc. In this paper we demonstarte that the combination of genetic algorithms with cascade correlation network seems to be able to detect the delayed gastric emptying from cutaneous EGGs.

Table 1
Results of tests on 78 new cases for networks with different hidden units developed by GCCA

Number of hidden units	%CC	SE (%)	SP (%)
2	80	79	82
3	83	84	82
7	76	71	82

The feature selection of surface EGGs 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 (90.0±1.0% vs 77.8±2.2%, $p<0.001$ for patients with normal and delayed gastric emptying in the fed state, for example), the percentage of tachygastria (4.1±0.6% vs 13.9±1.8%, $p<0.001$, patients with delayed gastric emptying in the fed state had significantly higher level) and the postprandial increase in EGG dominant power (4.6±0.5 dB vs 1.2±0.6 dB, $p<0.001$, the increase was significantly lower in patients with delayed gastric emptying). The size of the training set in this study is equal to that of the testing set. We use the balanced training and testing set so as to conveniently compare with the previous result obtained by BP algorithm [4].

Although the diagnosis result for this approach is comparable with that obtained by the BPNN, the main advantage of the GCCA over the BP algorithm is that it can automatically grow the architecture of neural networks to give a suitable network size for a specific problem. This feature makes the GCCA very attractive for real world applications. In addtion to no need to guess the size and connectivity pattern of the network in advacnce, speedup of the GCCA over the BP is another benefit. This is because in the BP algorithm each training case requires a forward and a backward pass through all the connections in the network; the GCCA requires only a forward pass and genetic search of limited generations, and many training epochs are run while the network is much smaller than its final size.

In summary, the proposed method seems to be a potentially useful tool for the automated diagnosis of delayed gastric emptying. Further research in this field will include adding more EGG parameters as inputs to the network to improve the performance.

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