Spectral Analysis of Episodic Rhythmic Variations in the Cutaneous Electrogastrogram

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***Abstract*—Electrical activity of the stomach can be measured using surface electrodes. The cutaneous recording of gastric electrical activity is called the electrogastrogram (EGG). Gastric electrical dysrhythmic events associated with abnormal conditions of the stomach may be detected from the EGG. An adaptive spectral analysis method which is based on autoregressive moving average modeling has previously been developed. The aim of this paper is to demonstrate the ability of the previous method in detecting gastric dysrhythmic events from the EGG. A series of bench tests simulating typical prohlems with the analysis of nonstationary electric potentials was conducted. The application of the adaptive spectral analysis method to dysrhythmic events and rhythmic variations of the gastric slow wave is presented in this paper. The adaptive spectral analysis approach provides several advantages: narrow frequency peaks permitting more precise frequency identification, determination of changes in frequency components at any time point, and enhanced interpretation of cutaneous EGG recordings.**

I. INTRODUCTION

THE normal frequency of the human electrogastric slow wave is about 3 cycles/min (cpm). Pacing the contractions of the stomach, it originates in a putative pacemaker region near the junction of the proximal one third and the distal two thirds of the gastric body along the greater curvature and is characterized by regularly recurring potentials propagating distally with increasing amplitude and velocity to the pylorus. Gastric electrical dysrhythmia includes tachygastria (from 4.5–9.0 cpm), bradygastria (frequency less than 2.0 cpm) and arrhythmia (irregular or absent rhythmic activity).

Although the relationship between electrical dysrhythmia and gastric dysmotility remains incompletely understood, evidence linking the two has been reported. Gastric electrical dysrhythmia was first recorded in dogs by Code and Marlett in 1974 [1] and in humans by Telander *et al.* in 1978 [2]. Tachygastria has been observed in conditions associated with nausea, vomiting, abdominal pain [3]–[5], and motion sickness [6]. Bradygastria was found in association with strong antral contractions in dogs [7]. Both tachygastria and bradygastria of short duration have been observed in postprandial electrogastrogram (EGG) recordings [8]–[11], most frequently in patients with gastric motility disorders [12], [13].

There is accumulating evidence that gastric dysrhythmia is usually of brief duration. For example, in a study investigating inhibition of prostaglandin synthesis effects on epinephrine-induced gastroduodenal electromechanical changes in humans, Kim *et al.* [14] observed short bursts of both tachygastria and bradygastria, and found that the median duration of these dysrhythmic episodes ranged from 2 to 10 min.

Gastric electrical activity can be recorded with cutaneous electrodes placed on the abdomen over the stomach and is known as the EGG [15]. Unlike internal gastric myoelectrical recordings, the EGG combines gastric electrical activity with noise artifact from sources such as respiration and motion. Several alternative recording techniques [16]–[19] and time-domain signal analysis methods have been developed [20]–[22] to enhance the signal-to-noise ratio in EGG recordings. Many frequency analysis techniques have been applied to the EGG signal in an effort to extract rhythmic information about gastric electrical activity. These techniques include the fast Fourier transform (FFT) [23], phase-lock filtering [24], autoregressive modeling [25], and pattern recognition [26]. Unfortunately, all of these methods process EGG data in a batch manner, leaving temporal analysis concerning rhythmic variations obscured.

To simultaneously reveal both the frequency components in an EGG signal and the temporal features of variations in frequency components, Van der Schee and Grashuis [27] proposed a running spectral analysis method applying the traditional short-time Fourier transform. The major drawback inherent in the short-time Fourier transform is that a tradeoff is inevitable between temporal and spectral resolution [28]. If one uses a longer sliding time window to obtain higher spectral resolution, the underlying nonstationarity will be smeared out, resulting in lower temporal resolution. Conversely, using a shorter window to achieve better temporal resolution will give lower spectral resolution. As an alternative to overcome this shortcoming of the short-time Fourier transform, a number of papers have been published on time-frequency analysis methods [29]–[33]. The Wigner distribution is one of the commonly used methods. It possesses very high resolution in both time and frequency. Its major drawbacks are that it is not necessarily nonnegative and produces cross terms between two signal components located at different regions in the time-frequency plane. No application of these methods has been reported in the EGG.

An adaptive spectral analysis has been developed, which is based on autoregressive moving average (ARMA) modelling [11]. It uses a so-called adaptive ARMA filter to estimate the instantaneous frequency of a time series. The aim of this paper was to demonstrate the ability of the previous method in detecting gastric dysrhythmic events from the EGG. A series of bench tests simulating typical problems with the

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analysis of nonstationary electric potentials was conducted. The application of the adaptive spectral analysis method to dysrhythmic events and rhythmic variations of the gastric slow wave is presented in this paper.

II. Adaptive Spectral Analysis Method

In the simplest of terms, the process of estimating the power spectrum of an EGG signal with adaptive spectral analysis entails first modelling the EGG signal using appropriate parameters and then computing the power spectrum based on these model parameters. By way of background, note that a time series with peak spectral components, such as a series of digitized EGG signal, can be modelled as an auto-regressive moving average (ARMA) process [34]. Theoretically, a signal, $s_j (j$: time instant) can be generated by exciting an ARMA process using a random time-series, n_j. Mathematically, it can be written as follows:

$$s_j = -\sum_{k=1}^{p} a_k s_{j-k} + \sum_{k=1}^{q} c_k n_{j-k} + n_j$$

$a_k\,(k = 1, 2, \cdots, p)$ and c_k, $(k = 1, 2, \cdots, q)$ are called the ARMA parameters. The power spectrum of the signal, s_j, can be calculated from these ARMA parameters.

To model an EGG signal, x_j, one simply proceeds in the opposite direction. By constructing a so-called adaptive ARMA filter (see Fig. 1, z^{-1} stands for one sample delay), the output signal, y_j, now approximates the input signal, x_j. It is expressed as [11]:

$$y_j = \sum_{k=1}^{p} a_{kj} x_{j-k} + \sum_{k=1}^{q} c_{kj} e_{j-k}$$

where e_j is the estimation error:

$$e_j = x_j - y_j.$$

Defining feed-forward and feedback vectors A_j and C_j, and feed-forward and feedback input vectors X_j and E_j as

$$X_j^T = [x_{j-1}, \cdots, x_{j-p}], E_j^T = [e_{j-1}, \cdots, e_{j-q}]$$
$$A_j^T = [a_{1j}, \cdots, a_{pj}], C_j^T = [c_{1j}, \cdots, c_{qj}]$$

the output of the adaptive filter y_j can be written as

$$y_j = A_j^T X_j + C_j^T E_j$$

and the error signal as

$$e_j = x_j - A_j^T X_j - C_j^T E_j.$$

Applying the steepest descent method and approximating the gradients of the mean squared error with respect to the filter parameters by the gradient of the squared error, we have,

$$A_{j-1} = A_j - \mu_a \frac{\partial E_j^2}{\partial A_j}$$
$$C_{j-1} = C_j - \mu_c \frac{\partial E_j^2}{\partial C_j}.$$

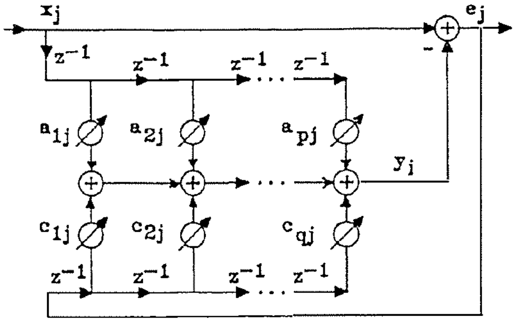

Fig. 1. The detailed structure of the adaptive ARMA filter.

To have a simple adaptation algorithm we assume that the feedback input vector E_j is not a function of the filter parameters. Under this assumption the least mean squares (LMS) algorithm can be easily derived and is expressed as follows:

$$A_{j+1} = A_j + 2\mu_a e_j X_j$$
$$C_{j+1} = C_j + 2\mu_c e_j E_j$$

or,

$$a_{k,j+1} = a_{k,j} + 2\mu_a e_j x_{j-k}, \quad k = 1, 2, \cdots, p$$
$$c_{k,j+1} = c_{k,j} + 2\mu_c e_j e_{j-k}, \quad k = 1, 2, \cdots, q$$

where step-sizes, μ_a and μ_c, are constants with values less than the reciprocal of $(X_j^T X_j + E_j^T E_j)$. The algorithm states that the filter parameters at each successive time step, $a_{k,j+1}$ and $c_{k,j+1}$, are equal to their current values, $a_{k,j}$ and $c_{k,j}$, plus a modification term. The number of the filter parameters is equal to $q + p$. In our experience, the best value for q was found to be in the range of 2–10 for spectral analysis of EGGs [11]. The value of p must be greater than or equal to the number of digitized points that span the longest rhythmic cycle of interest in the signal. For example, if the period of the rhythmic component of interest in an EGG is 20 s (0.05 Hz or 3.0 cpm), and the sampling frequency is 2 Hz, the smallest value of p should be 40. The requirement of this large value is attributed to the nature of the LMS algorithm [41].

Once the adaptive filter converges, the power spectrum of the input signal x_j can be calculated from the filter parameters according to the following:

$$P_j(\omega) = \frac{\sigma^2 \left|1 + \sum_{k=1}^{q} c_{kj} \exp(-i\omega k)\right|^2}{\left|1 + \sum_{k=1}^{p} (-a_{kj}) \exp(-i\omega k)\right|^2}, i = \sqrt{-1}$$

where σ^2 is calculated as follows:

$$\sigma^2 = \frac{1}{j - m + 1} \sum_{k=m}^{j} e_k^2$$

where j is the current time index and m is the time index at which the algorithm converges.

At any point in a time series, a power spectrum can be calculated instantaneously from the updated parameters of the model. Similarly,the power spectrum of the signal for any particular time interval can be calculated by averaging the filter parameters over that time interval. Since the parameters are initially set to zero, the adaptive filter needs an initial period of time to converge, the power spectrum for the initial time period is unavailable. This problem is circumvented by processing the initial section of a time-series twice. The values of the parameters reached at the end of the first run can be utilized to initialize the model during the second run.

III. SIMULATION RESULTS

A series of bench tests simulating common problem situations in the analysis of gastric myoelectric events of typically brief duration were conducted to examine the performance of the adaptive ARMA spectral analysis method. Four types of electrical dysrhythmias were simulated by generating normal 3 cpm signals, embedded in which were 2-min episodes of: 1) "tachygastria" (7 cpm), 2) a "pause" (0 cpm), 3) "bradygastria" (1.5 cpm) and 4) a frequency-modulated signal. The tachygastrial and pause signals were each interposed between 6.00-min and 6.27-min epochs of 3 cpm activity. The 2-min bradygastrial signal was superimposed on Minutes 7 and 8 of a 14.27-min long period of continuous 3 cpm activity. The simulated signals for each situation were subjected to spectral analysis using the adaptive method. The parameters of the adaptive method were as follows: $p = 40, q = 2, \mu_a = \mu_c = 0.01/(X_j^T X_j + E_j^T E_j)$.

Tachygastria

Panel (a) in Fig. 2 displays the simulated EGG signal consisting of 6 min of regular 3 cpm activity followed by a 2-min "episode" of simulated tachygastria at 7 cpm in the absence of 3 cpm activity. This is then followed by another period of 3 cpm activity lasting 6.27 min. A power spectrum of the entire 14.27-min signal using the conventional periodogram method is shown in Fig. 3. Two distinct frequency components, at 3 cpm (0.05 Hz) and 7 cpm (0.117 Hz), are clearly discernable. However, time information concerning the brief emergence and evanescence of the tachygastria episode is inherently unavailable. The results of the adaptive method are shown in Fig. 2(b). Here the power spectra were computed every 30 s starting at the fourth minute with each curve from the bottom to the top in the figure representing a power spectrum analysis of 30 s of data. These 30-s analyses are ordered serially without overlap. Comparing these results with the simulated signal in (a) one can observe that the frequency component of interest can be precisely linked to particular time points. The spectra for minutes 6 to 8 (represented by the 6th through the 9th curves from the bottom) show frequency peaks appropriately and precisely at 7 cpm while the preceding and succeeding curves show a frequency peak at 3 cpm. The temporal ordering of frequency events in the simulated signal is accurately retained in the spectral analysis produced by the adaptive method. In addition, the adaptive method produced narrow frequency peaks in the power spectra in a highly distinct manner.

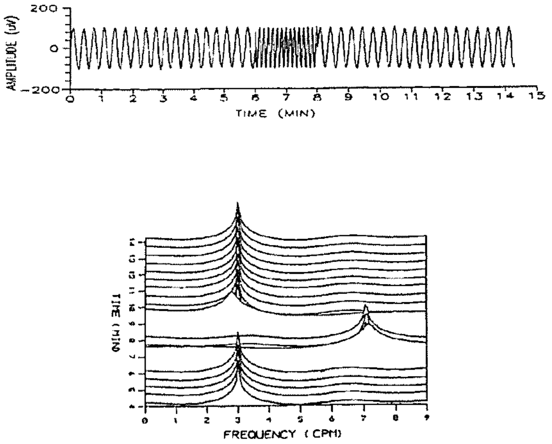

Fig. 2. Spectral analytic determination of a simulated episode of tachygastria. Panel (a) shows the simulated EGG signal containing a 2-min segment of 7 cpm activity interposed between segments of 3 cpm activity. Panel (b) displays power spectra calculated using adaptive spectral analysis for every 30 s beginning after 210 s.

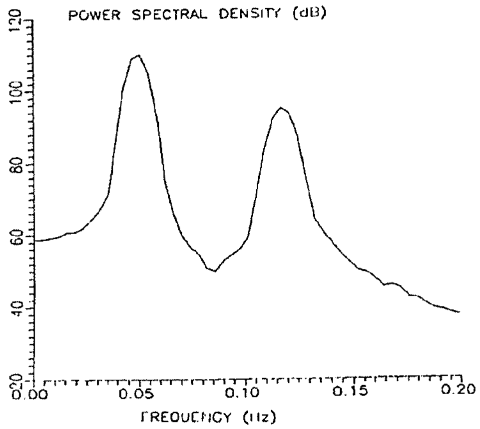

Fig. 3. Power spectrum for the 14.27-minute data shown in Fig. 2(a) using the periodogram method. Two frequency components (3 cpm and 7 cpm) are prominent but time information is lost.

Pauses

Pauses in cutaneous EGG recordings are not uncommon [35]. For unknown reasons, the gastric slow wave in an EGG recording may wax and wane frequently, and disappear for a short period following tachygastria. The computer-generated signal shown in Fig. 4(a) simulates a pause lasting 2 min between minutes 6 and 8 and interposed between otherwise ongoing, regular 3 cpm activity. It can be seen in (b) that the pause in the raw signal has a distinct onset and offset which can be localized in time. The pause itself is appropriately represented by uniformly flat power spectra during minutes 6 to 8.

Bradygastria

Bradygastria has frequently been detected at our laboratory in postprandial EGG recordings where it is usually superimposed on the normal slow wave. The simulated signal

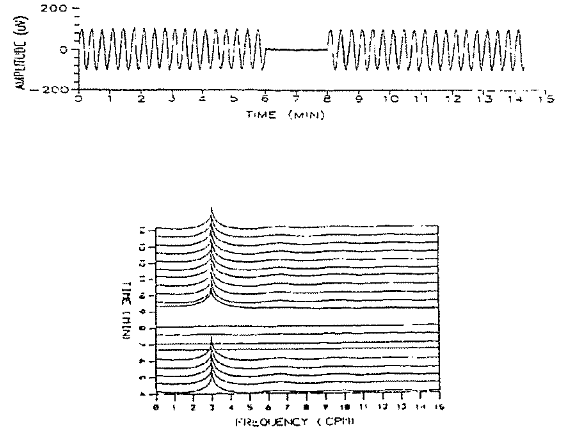

Fig. 4. Spectral analytic determination of a simulated episode of a "pause" in ongoing 3 cpm activity. Panel (a) displays the simulated EGG signal. Panel (b) displays the power spectra calculated using the adaptive method.

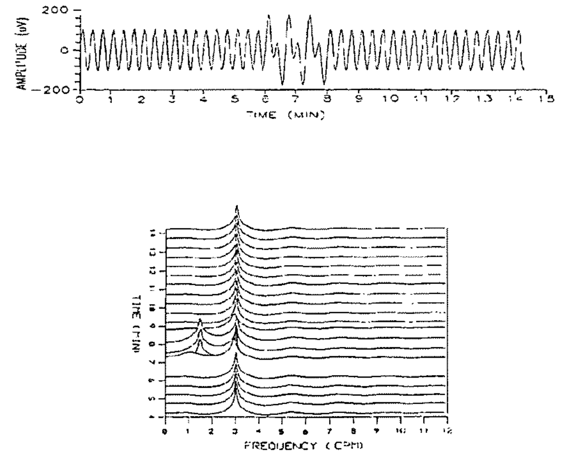

Fig. 5. Spectral analytic determination of a simulated episode of bradygastria. Panel (a) displays the simulated EGG signal with a segment of bradygastria superimposed upon ongoing 3 cpm activity. Panel (b) displays spectra calculated using the adaptive method.

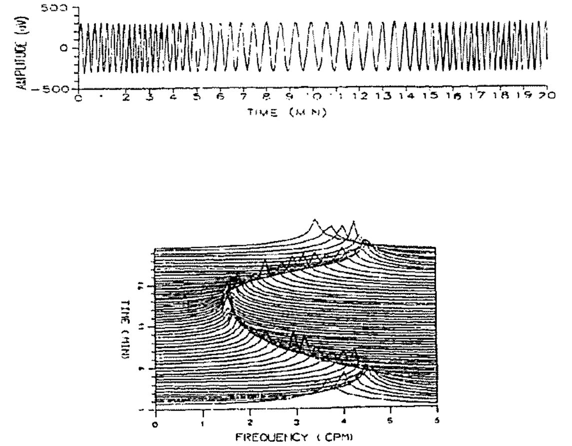

Fig. 6. Spectral analytic determination of a simulated episode of a shift or instability in the ongoing slow wave frequency. Panel (a) displays the simulated EGG signal. Panel (b) displays the power spectra calculated using the adaptive method every 20 s.

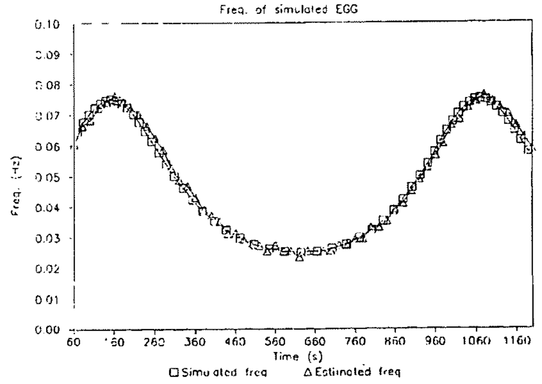

Fig. 7. Instantaneous determination of the frequency of the simulated signal shown in Fig. 6 comparing actual frequency with frequency calculated using the adaptive method.

illustrated in Fig. 5(a) shows bradygastric activity (1.5 cpm), 2-min in duration, superimposed on a 14.27-min segment of ongoing 3 cpm activity. It can be seen in (b) that the 3 cpm activity is accurately estimated by the adaptive spectral analysis method. The 1.5 cpm episode is clearly represented by sharp peaks in minutes 6.5 through 8. It is notable that the power spectrum for the first 30-s period following the onset of the 1.5 cpm episode in (b) shows no well defined frequency peak. This outcome ocurred because the 30-s data window included only three quarters of the initial cycle of bradygastria, too little for the adaptive analysis algorithm to completely converge.

Frequency Modulated Signal

The normal frequency of the gastric slow wave is about 3 cpm. After eating and drinking, the frequency of the gastric slow wave changes as will be shown later in the next section. Fig. 6 dispalys a 20-min computer-generated signal representing a simulated rhythmic shift in the gastric slow wave in which the dominant slow wave frequency gradually changes at a continuous rate from 1.5 to 4.5 cpm. It can be seen in (b) that the spectrum produced by the adaptive method provided a series of sharply distinct frequency peaks that permit clear tracking of the frequency shift in the slow wave. Frequency tracking can also be accomplished using the adaptive method by plotting target frequency values such as the slow wave as a function of time. An example is displayed in Fig. 7 where both actual frequency values for the simulated signal and estimates from the adaptive analysis are plotted. The high degree of overlap suggests that a fine-grained analysis of frequency components is possible with the adaptive method.

IV. RESULTS OF REAL EGG APPLICATIONS

Measurement of the Electrogastrogram

Spectral analysis by the adaptive method was also performed on EGG recordings obtained from selected normal volunteers and patients. EGG measures for this sample were obtained as follows. First, the stomach was localized ultrasonically using a 5 MHz linear array transducer. Orientation of the distal stomach was marked on the abdominal surface. Skin sites were abraded to reduce electrode-to-skin impedance to less than 10 kΩ. The volunteers were lying in supine position and were asked not to talk or move during the measurement. Three active electrodes were positioned on the abdomen along the antral axis of the stomach (with an interelectrode space of 3.5 cm) and one common reference electrode was placed 6 cm away in the upper right quadrant. Three bipolar electric signals were obtained by connecting each individual active electrodes with the common reference electrode. The EGG signal was amplified and filtered (0.02 to 0.3 Hz, 6 dB/octave), and then displayed on a strip chart recorder (Sensormedics) and simultaneously digitized with a 12-bit eight channel A/D converter, and stored on an IBM-AT computer with a sampling frequency of 2 Hz. The parameters of the adaptive filter were as follows: $p = 40, q = 2, \mu_a = \mu_c = 0.01/(X_j^T X_j + E_j^T E_j)$.

Detection of Tachygastria and Pause

Fig. 8(a) displays a segment (8-min) of an EGG recording obtained from a healthy female after a drink of 140 ml milk (10.5% fat). Tachygastria is evident during minute 4 and is followed by a 1-min pause. The running spectra of this segment of the EGG using the adaptive method are presented in (b) where each frequency spectrum represents an analysis for a serial 1-min period of the raw EGG signal. It can be seen that tachygastria at about 8 cpm emerges during the fourth minute and no clear peaks are present in the subsequent minute indicating a pause following the tachygastria. Normal slow wave activity at 3 cpm appears during the final 2 min of this segment.

Pre- and Postprandial EGG Analysis

Results of an experimental study investigating pre- and postprandial response of the EGG are presented in Table I. Variations of both amplitude and frequency of the EGG after drinking 140 mL water and consuming a solid meal (600 kcal) can be observed. Preprandially, the EGG had a frequency (over 20 min) of 3.18 cpm and a power of 46.4 dB. After drinking water, the frequency of the EGG varied but its average over 20 min (3.14 cpm) was similar to the preprandial value (3.18 cpm) while the power increased to 51.0 dB (an increase of 6 dB in power is equivalent to a 100% increase in amplitude). After eating the test meal, both the amplitude and frequency of the EGG increased. The average frequency over 60 min was 3.6 cpm which was 0.42 cpm higher than the preprandial value. The average power for serial 20 min periods was 55.6, 53.8, and 50.8 dB, respectively. The spectral power of the gastric slow wave decreases as chyme from the stomach is expelled to the small bowel.

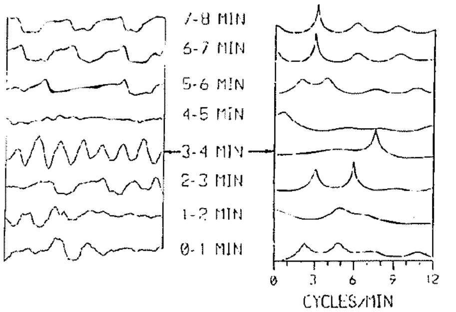

Fig. 8. Example of application of adaptive spectral analysis to an 8-min cutaneous EGG recording obtained from a healthy adult female before and after drinking 140 mL of milk (10.5% fat content). An episode of tachygastria emerged during minute 4. Panel (a) displays the raw minute-by-minute EGG signal; panel (b) displays the corresponding power spectra. A shift to and then from 3 cpm activity is revealed during minute 3 while clear 8 cpm activity dominates minute 4. This is followed by a pause in rhythmic activity during minute 5.

TABLE I
MEAN EGG FREQUENCY AND POWER AS A FUNCTION OF TIME AND CONDITION

	Time (min)					
Condition	4	8	12	16	20	Mean ± SD
			Frequency (cpm)			
Fasted (0-20 min)	3.2	3.2	3.1	3.2	3.2	3.18 ± 0.04
Post-Water (0-20 min)	2.8	3.5	3.4	2.8	3.2	3.14 ± 0.33
Post-Meal (0-20 min)	3.7	3.6	3.6	3.6	3.6	3.64 ± 0.04
Post-Meal (20-40 min)	3.7	3.6	3.7	3.7	3.6	3.64 ± 0.05
Post-Meal (40-60 min)	3.5	3.6	3.8	3.7	3.2	3.56 ± 0.23
			Power (dB)			
Fasted (0-20 min)	43	44	41	52	52	46.4 ± 5.2
Post-Water (0-20 min)	57	47	48	49	54	51.0 ± 4.3
Post-Meal (0-20 min)	60	55	56	54	53	55.6 ± 2.7
Post-Meal (20-40 min)	49	62	52	54	52	53.8 ± 4.9
Post-Meal (40-60 min)	54	52	50	51	47	50.8 ± 2.6

Note: EGG recording obtained in an asymptomatic female adult.

EGG's from Normals and Gastroparetic Patients

The running spectra of the EGG using the proposed method provide important information in the clinical diagnoses of patients with suspected gastric motility disorders. In a recent study [36], we applied the adaptive spectral analysis method to analyze EGG recordings obtained in 24 normal subjects and 27 patients with gastroparesis. The EGG was defined as abnormal if more than 30% of the total recording showed an absence of 2–4 cpm slow waves. The assessment was performed as follows: Each EGG recording (120-min) was divided into 2-min blocks. The power spectrum of each 2-min EGG was calculated by the adaptive method, yielding 60 consecutive power spectra for each recording. To determine whether each 2-min EGG had normal slow waves its corresponding power spectrum was examined by a frequency peak detection program: if there was no peak in the range of 2–4 cpm, the 2-min EGG was said to be abnormal. If more than 30% of

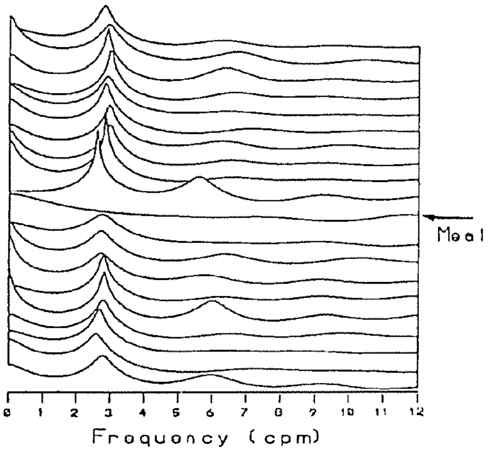

Fig. 9. An example of application of adaptive spectral analysis to cutaneous EGG recording obtained from a normal female before and after a solid test meal. Each spectrum represents analysis of serial 2-min periods of EGG data. Sharp peaks at 3 cpm indicate regular, robust, and normal slow wave activity.

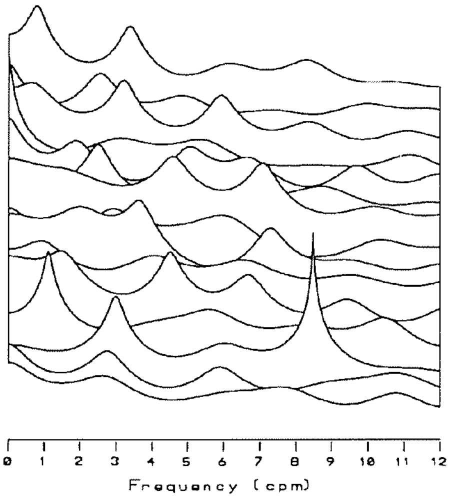

Fig. 10. Application of adaptive spectral analysis to a cutaneous EGG obtained from a fasted, nauseated individual with gastroparesis. Each spectrum represents analysis of a serial 2-min period of EGG data.

the power spectra showed no peaks in the range of 2–4 cpm the EGG was said to be abnormal. The results showed that all 24 normal subjects had regular gastric slow waves (see Fig. 9 for an example) but 20 of the 27 patients showed irregular slow waves (see Fig. 10 for an example).

V. DISCUSSION

Previous studies [35], [37] have shown that the noninvasive EGG is a reliable measure of electrical activity of the stomach. Since electrical dysrhythmia is usually associated with motor disorders of the stomach, the detection of dysrhythmia from the EGG is of great interest. To detect gastric dysrhythmia, Van der Schee and Grashuis [27] proposed a running spectral analysis method applying the short-time Fourier transform, and showed that a dysrhythmic event of 64 seconds can be identified from the EGG using the method. The adaptive spectral analysis method described in this paper was previously published in [11]. The previous paper presented the performance of the adaptive method in comparison with an FFT method and with an autoregressive model, the convergence property of the algorithm, the optimization of parameters such as, step-size, μ_a and μ_c, and the AR and MA orders. The algorithm for the adaptive ARMA filter was similar to the LMS algorithm Widrow *et al.* described in [38].

The aim of this paper was to demonstrate the ability of the adaptive spectral analysis method in the detection of gastric electrical dysrhythmia from the electrogastrogram. Gastric dysrhythmia includes tachygastria, bradygastria, and arrhythmia. In this paper, a series of tests simulating typical dysrhythmic events, such as tachygastria, bradygastria, and pause, has been conducted. The presented results demonstrated the ability of the adaptive spectral analysis method in the detection of dysrhythmic events of brief duration. The simulation results have shown that the adaptive spectral analysis method provides several advantages: 1) Narrow peaks in the power spectra, clearly indicating the presence of distinct frequency components and giving an enhanced interpretation of the EGG recording. 2) Ability to compute the power spectrum not only at any particular time interval but at any particular time instant, thereby resulting in the instantaneous determination of the rhythmic variation. As shown previously, different types of dysrhythmic events of brief duration (2 min) as well as the continuous variation of the simulated slow wave were precisely detected. 3) Ease of use and capability for on-line data analysis.

This paper has shown the application of the adaptive spectral analysis method in clinical electrogastrography. Although the first EGG recording was made a long time ago in 1922, the clinical application of the EGG has been very limited. One of main reasons is the difficulty in extraction of relevant information from the EGG, which usually has a low signal-to-noise ratio. Dysrhythmic events are often of brief duration and embedded in noisy EGG recordings. In this paper, we have demonstrated the following: a) dysrhythmia of brief duration can be detected from the EGG using the adaptive spectral analysis method; b) the response of gastric electrical activity to exogenous stimuli can be measured from the EGG using the adaptive spectral analysis method. An example was shown on the response of the EGG to a test meal in a normal subject. Using the adaptive spectral analysis method we have observed different responses of the EGG between normal subjects and patients with suspected motor disorders of the stomach [36]. Similarly, using the method we are able to measure the response of gastric electrical activity to pharmacological and prokinetic agents, e.g., whether the agent induces dysrhythmia or normalize dysrhythmia [39]; c) as presented in the results section, the adaptive spectral analysis method enables us to compute the percentage of the normal (or abnormal) electrical activity in an EGG recording, and to define whether the EGG recording was normal or abnormal. Therefore, the cutaneous EGG can be used to assess whether the subject has normal or abnormal gastric electrical activity.

Running spectral analysis based on short-time Fourier transform has been widely used for frequency analysis of gastric electrical dysrhythmia [12], [27], [40]. However it is limited by its inherent drawback of tradeoff between temporal and spectral resolution. Several minutes of data are required to accurately compute a power spectrum of the EGG. Each power spectrum provides ensemble information of the signal. As such, any rhythmic variation within these several minutes cannot be detected and the exact time information of the rhythmic variations is not available.

In conclusion, this paper has shown that the adaptive spectral analysis method is powerful and very useful in analyses of cutaneous EGG recordings, especially in detecting dysrhythmic events and rhythmic variations of the gastric slow wave in a cutaneously measured electrogastrographical signal.

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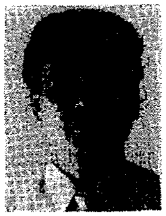

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