Optimal Wavelets for Electrogastrography

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Abstract

Matching a wavelet to class of signals can be of interest in feature detection and classification based on wavelet representation. The aim of this work is to provide a quantitative approach to the problem of matching a wavelet to electrogastrographic (EGG) signals. Visually inspected EGG recordings from sixteen dogs and six volunteers were submitted to wavelet analysis. Approximated wavelet-based versions of EGG signals were calculated using Pollen parameterization of 6-tap wavelet filters and wavelet compression techniques. Wavelet parameterization values that minimize the approximation error of compressed EGG signals were sought and considered optimal. The wavelets generated from the optimal parameterization values were remarkably similar to the standard Daubechies-3 wavelet.

Keywords

Electrogastrography, gastric electrical activity, matching wavelets, optimization techniques.

1 INTRODUCTION

Cutaneous recordings of gastric electrical activity (GEA) known as electrogastrography (EGG), can play a major role in the diagnosis of gastric motility disorders [1]. Because of its low-cost and non-invasiveness, the EGG technique has great appeal as a clinical tool and has been related to various gastric motility abnormalities [2]. Multiple studies have been conducted in other to analyze EGG recordings. Although signal processing of EGG signals has been considered essential for extracting clinically relevant information, various traditional methods have been utilized with limited success [3].

Recently, advanced signal processing techniques, such as wavelets, have been employed to analyze electrogastrograms [4–8]. This approach has been used to (i) propose new wavelets that can offer a better time-frequency localization of EGG recordings [4–5]; (ii) perform noise detection in EGG signals [6]; (iii) cancel artifacts related to stimulation [7]; and (iv) characterize global gastric electrical dysrhythmias [8]. An important aspect of wavelet analysis is related to designing a wavelet that matches a class of signals. Although wavelet matching can be of great importance for detection and classification [9], wavelets that match EGG signals have not been systematically sought.

The present study addresses the problem of finding a wavelet that best “matches” the waveshape of EGG signals in basal state. Although there are numerous issues concerning the choice of wavelet for signal analysis [9], generally, a wavelet can be regarded as best suited to a class of signals if the latter can be represented by as few wavelet coefficients as possible [10,11]. Thus, wavelets which resemble the waveshape of the signal under analysis are often selected.

In the framework of the proposed research methodology, an optimal wavelet is sought that can adequately represent a wavelet-compressed EGG signal at a given compression ratio. The optimality is detected by minimizing an error measure between the original signal and its compressed version, subject to the choice of wavelet. If, for a given wavelet, the error associated with the compressed signal were minimal, then its wavelet coefficients were considered to best represent the original signal. Therefore, the selected wavelet would more effectively “match” the signal under analysis when compared to other wavelets in consideration [12].

Consequently, the ultimate aim of this study is to quantitatively determine a wavelet suitable for the analysis of basal EGG recordings in canine and human models.

2 METHODS

2.1 EXPERIMENTAL SETUP

2.1.1 CANINE EXPERIMENTS

After a laparotomy and the installment of six pairs of internal subserosal stainless steel wire electrodes into the antral gastric wall of sixteen acute dogs (seven female and nine male), the abdominal wall was closed and five neonatal electrodes (Con-
A sampling frequency of 10 Hz and Lfication, 12-bit analog-to-digital conversion was performed using 0.2 Hz low-pass first order Butterworth active filter. After amplification, the raw EGG data were intermittently contaminated with a multitude of artifacts, including: (i) motion artifacts; (ii) spontaneous variations in electrode potentials; (iii) respiration; (iv) signal saturation during recording; (v) electrocardiac activity; and (vi) loss of signal during recording. Usually these artifacts appeared simultaneously in all recording channels. Some of these noisy patterns were visually evident (e.g., iv and vi) and could be easily identified and discarded [3]. This practice has been recommended before in order to obtain a more reliable signal for subsequent analysis [13].

Therefore, for each subject, a 10-minute time interval of channel-synchronized data was manually selected. These data were considered to be free from identifiable noise patterns.

### 2.1.3 Signal Preprocessing

Since both canine and human recordings were of significant duration, the raw EGG data were preprocessed via a Fast Wavelet Transform using Mallat’s pyramid algorithm for decomposition (forward transform) and reconstruction (inverse transform) [10].

Let \( x \) be a discrete signal with \( N = 2^J \) points (a sampled version of the analog signal \( x(t) \)). The discrete wavelet transform (DWT) of \( x \) is computed in a recursive cascade structure consisting of decimators \( J \) and complementing filters \( h \) (low-pass) and \( g \) (high-pass), which are uniquely associated with a wavelet [14]. Fig. 2 depicts a diagram of the filter bank structure.

At the end of the algorithm computation, a set of vectors is obtained \( \{d_1, d_2, \ldots, d_J, a_0\} \), where \( J \) is the number of decomposition levels (scales) of the DWT. This set of approximation and detail vectors represents the DWT of the original signal. Vectors \( d_j \) contain the DWT detail coefficients of the signal in each scale \( j \). As \( j \) varies from 1 to \( J \), a finer or coarser detail coefficient vector is obtained. On the other hand, the vector \( a_0 \) contains the approximation coefficients of the signal at scale \( J_0 \). It should be noted that this recursive procedure can be iterated \( J \) times at most. Usually, the procedure is iterated \( J_0 < J \) times. Depending on the choice of \( J_0 \), a different set of coefficients can be obtained. Observe that the discrete signal \( x \) and its DWT have the same length \( N \). The inverse transform can be performed using a similar recursive approach [10]. Generally, a signal can be subject to various wavelet decompositions. The analysis depends on (i) the choice of wavelet (filters \( h \) and \( g \)); and (ii) the number of decomposition levels (scales) \( J_0 \).

A wavelet-based compression scheme aims to satisfactorily represent an original discrete signal \( x \) with as few DWT coefficients as possible [11, 15, 16]. One simple and effective way of doing that is to discard the coefficients that, under certain criteria, are considered insignificant. Consequently, the signal reconstruction is based on a reduced set of coefficients [11, 17].

In the present work the classic scheme for non-linear compression was used [11]. This procedure considers an \textit{a posteriori} adaptive set, which keeps \( M \) wavelet transform coefficients that have the largest absolute values. A hard thresholding was used

| Channel | Electrode Combination |
|---------|-----------------------|
| 1       | a–b                   |
| 2       | c–d                   |
| 3       | e–f                   |
| 4       | g–h                   |
| 5       | i–j                   |
| 6       | k–l                   |

| Channel | Electrode Combination |
|---------|-----------------------|
| 7       | 1–2                   |
| 8       | 2–3                   |
| 9       | 3–4                   |
| 10      | 4–5                   |
| 11      | 1–3                   |
| 12      | 1–4                   |
| 13      | 2–5                   |
| 14      | 1–5                   |

Figure 1: Internal (a) and cutaneous (b) electrode positioning in canine experiments. Various electrode combinations were used for the GEA (c) and the EGG (d) recordings. The electrode combination for the EGG recordings in human experiments was similar.

### 2.1.2 Human Experiments

Using a similar 8-channel EGG configuration, one-hour recordings from six normal volunteers (two female, four male) in post-prandial state (500 Kcal, 52% carbohydrates, 19% proteins, and 29% fat) were obtained. The average body mass index for the volunteers was 22.2 kg·m⁻² (SD 3.0 kg·m⁻²). Signal conditioning, amplification and digitization process similar to the ones utilized in the canine experiments were implemented.

All experiments were approved by the Animal Welfare Committee and the Ethics Committee at the Faculty of Medicine, University of Alberta.
to set the remaining coefficients to zero. The number of coefficients $M$ to be retained was determined according to the desired compression ratio $CR$, which was defined by

$$CR = \frac{N}{M},$$

where $N$ and $M$ are the number of wavelet transform coefficients of the original and the compressed signals, respectively.

### 2.2.2 Measurement of Distortion

To further the analysis, it is necessary to introduce an error measure to compare the original discrete signal $x$ with its reconstruction $\hat{x}$. Several measures that allow the evaluation of the effect of compression schemes have been suggested [18]. However, one of the most commonly used is the Percent Root-mean-square Difference (PRD) [15, 16, 18], which was utilized in the present study as a measure of distortion in the compression scheme. The PRD of two signals, $x$ and $\hat{x}$, both of length $N$, is defined by:

$$PRD(x, \hat{x}) = \sqrt{\frac{\sum_{i=0}^{N-1} (x_i - \hat{x}_i)^2}{\sum_{i=0}^{N-1} x_i^2}} \times 100\%.$$

### 2.3 Choice of Parameters

#### 2.3.1 Number of Scales

In order to select the number of scales $J_0 \in \{1, \ldots, J\}$ of the wavelet transform decomposition, the following criterion was introduced: $J_0$ was chosen so that the coarsest approximation scale had a pseudo-frequency close to the EGG dominant frequency $f_c$ of 4–6 cycles per minute for the canine subjects [19] and 3 cycles per minute for the humans.

The pseudo-frequency $f_{\text{pseudo}}$ of a given scale $j$ is

$$f_{\text{pseudo}} = \frac{f_w}{j \cdot T_s}, \quad j = 1, 2, \ldots, J,$$

where $T_s$ is the sampling period (0.1 s) and $f_w$ is the center frequency of a wavelet (the frequency that maximizes the magnitude of the Fourier transform of the wavelet) [14]. Consequently, a scale $J_0$ was selected which minimized the difference $(f_{\text{pseudo}} - f_c)$. Table 1 shows the number of decomposition levels for some common wavelets.

#### 2.3.2 Compression Ratio

A compression ratio set $CR \in \{3, 5, 7, 10\}$ was selected and a matching procedure was carried out aiming at optimizing the choice of wavelet.

### 2.4 Optimization of the Wavelet Choice

In the context of the present study, a wavelet was sought that minimized the PRD between the original EGG signal and its reconstruction for a given compression ratio.

However, the abundance of wavelets [10] makes such approach prohibitive. As a result, some constraints on the choice of wavelet were introduced.

It is well known that wavelets can be generated from discrete finite impulse response (FIR) filters [14]. In the present work, the analysis was limited to wavelets generated by FIR filters with length no greater than six coefficients. In this subset of wavelets one may find Haar, Daubechies-2, Daubechies-3, and Coiflet-1 wavelets, to name the most popular ones [10].

This restriction is quite convenient, since all FIR filters of length up to six that can be utilized to generate wavelets have simple parameterizations of their coefficients [22]. For example, Pollen parameterization of 6-tap wavelet filters [21] has two independent variables $(a, b) \in [-\pi, \pi] \times [-\pi, \pi]$. Varying these two parameters, a filter that generates a new wavelet can be defined. Consequently, the Pollen parameterization defines a plane on which every point is connected to a wavelet [21].

Using the discussed compression scheme, one can compute a PRD value for each wavelet generated from a point with coordinates $(a, b)$ on the parameterization plane. Doing so, a surface can be defined by the points $(a, b, \text{PRD})$. Thus, the minima of this surface correspond to the point coordinates $(a, b)$ that generate a wavelet with good “matching” properties, since the PRD values at these minima are small.

As a result, a set of point coordinates $(a_i, b_i)$ could be determined on the parameterization plane, which minimizes the PRD for each EGG recording $i$. Fig. 3 shows typical surfaces generated for basal canine and human EGG signals.

Taking the mean value of the minima, the best wavelet parameterization $(a^*, b^*)$ could be defined. Thus, $(a^*, b^*)$ generates a wavelet that on average “matches” best the normal EGG recordings.

### 3 Results

The optimal values of the wavelet parameterization were determined for the selected compression ratios (Table 2). The values for compression ratio of 3 were associated with the wavelets

| Wavelet   | Canine | Human |
|-----------|--------|-------|
| Haar      | 7      | 8     |
| Daubechies-2 | 6      | 7     |
| Daubechies-3 | 7      | 7     |
| Coiflet-1 | 7      | 7     |

**Table 1: Number of decomposition scales $J_0$ for some wavelets**
Figure 3: Plots generated after computing the PRD surface for all possible wavelets on the parameterization plane, using a canine EGG signal with CR = 3 (a), and CR = 10 (b). A representative human EGG signal was used to build PRD surfaces with CR = 3 (c), and CR = 10 (d). The minimum value is depicted by a circle (○). The coordinate points that correspond to Haar (●), Daubechies-2 (×), Daubechies-3 (●), and Coiflet-1 (△) wavelets are shown. The axes are normalized by \( \pi \).
The problem of finding optimal wavelets to “match” EGG signals was quantitatively addressed. The proposed wavelets can be considered as tools to further EGG signal analysis. Moreover, the suggested methodology opens an avenue towards the classification of electrograms based on the PRD value of their wavelet compressed version, either applying the obtained optimal wavelets or the standard Daubechies-3.

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REFERENCES

[1] A. J. P. M. Smout, E. J. Van Der Schee, and J. L. Grashuis, “What is measured in electrogastrography?” Dig. Dis. Sci., vol. 25, no. 3, pp. 179–186, Mar. 1980.
[2] M. Bortolotti, “Electrogastrography: A seductive promise, only partially kept,” Amer. J. Gastroenterol., vol. 93, no. 10, pp. 1791–1794, Oct. 1998.
[3] M. A. M. T. Verhagen, L. J. Van Schelven, M. Samsom, and A. J. P. M. Smout, “Pitfalls in the analysis of electrogastrographic recordings,” Gastroenterology, vol. 117, no. 2, pp. 453–460, 1999.
[4] X. Xie and H. H. Sun, “Sinusoidal time-frequency wavelet family and its application in electrogram signal analysis,” in Proc. 20th Ann. Int. Conf. IEEE Eng. Med. Biol. Soc., vol. 3, Hong Kong, China, 1998, pp. 1450–1453.
[5] C. Ryu, K. Nam, S. Kim, and D. Kim, “Comparison of digital filters with wavelet multiresolution filter for electrogastrogram,” in Proc. Second Joint BMES/EMBS Conf., Houston, USA, Oct. 2000, pp. 137–138.
[6] J. Liang, J. C. Cheung, and J. D. Z. Chen, “Noise detection and denoising on electrogastrography using nonorthogonal multiresolution wavelet analysis,” in Proc. 18th Ann. Int. Conf. IEEE Eng. Med. Biol. Soc., vol. 3, Amsterdam, Netherlands, 1996, pp. 1039–1040.
[7] H. Liang and Z. Lin, “Stimulus artifact cancellation in the serosal recordings of gastric myoelectric activity using wavelet transform,” IEEE Trans. Biomed. Eng., vol. 49, no. 7, pp. 681–688, Jul. 2002.
[8] W. Qiao, H. H. Sun, W. Y. Chey, and K. Y. Lee, “Continuous wavelet analysis as an aid in the representation and interpretation of electrogram signals,” in Proc. 15th Southern Biomed. Eng. Conf., Dayton, USA, Mar. 1996, pp. 140–141.
[9] J. O. Chapa and R. M. Rao, “Algorithms for designing wavelets to match a specified signal,” IEEE Trans. Signal Processing, vol. 48, no. 12, pp. 3395–3406, Dec. 2000.
[10] S. G. Mallat, A Wavelet Tour of Signal Processing, 2nd ed. Academic Press, 1999.
[11] M. Vetterli, “Wavelets, approximation, and compression,” IEEE Signal Processing Mag., vol. 5, pp. 59–73, Sep. 2001.
[12] R. A. Gopinath, J. E. Odegard, and C. S. Burrus, “Optimal wavelet representation of signals and the wavelet sampling theorem,” IEEE Trans. Circuits Syst. II, vol. 41, no. 4, pp. 262–277, Apr. 1994.
[13] H. P. Parkman, W. L. Hasler, J. L. Barnett, and E. Y. Eaker, “Electrogastrography: a document prepared by the gastric section of the American motility society clinical GI motility testing task force,” Neurogastroenterology and Motility, vol. 15, pp. 89–102, 2003.
[14] M. Misiti, Y. Misiti, G. Oppenheim, and J.-M. Poggi, Wavelet Toolbox User’s Guide, 2nd ed. New York: The MathWorks, Inc., 2000.
[15] A. J. P. M. Smout, “Pitfalls in the analysis of electrogastrographic recordings,” Dig. Dis. Sci., vol. 25, no. 3, pp. 179–186, Mar. 1980.
[16] Z. Lu, D. Y. Kim, and W. Pearlman, “ECG signal compression with a new wavelet method,” in Proc. First Joint BMES/EMBS Conf., Troy, USA, Oct. 1999, p. 955.
[17] M. Unser and A. Aldroubi, “A review of wavelets in biomedical applications,” Proc. IEEE, vol. 84, no. 4, pp. 626–638, Apr. 1996.
[18] R. Besar, C. Eswaran, S. Sahib, and R. J. Simpson, “On the choice of the wavelets for ECG data compression,” in Proc. Int. Conf. Acous., Speech, and Signal Processing, Jun. 2000, pp. 1011–1014.

[19] M. P. Mintchev, A. Girard, and K. L. Bowes, “Nonlinear adaptive noise compensation in electrocardiograms recorded from healthy dogs,” IEEE Trans. Biomed. Eng., vol. 47, no. 2, pp. 239–248, Jan. 2000.

[20] H. Zhou and A. H. Tewfik, “Parametrization of compactly supported orthonormal wavelets,” IEEE Trans. Signal Processing, vol. 41, no. 3, pp. 1428–1431, Mar. 1993.

[21] A. H. Tewfik, D. Sinha, and P. Jorgensen, “On the optimal choice of a wavelet for signal representation,” IEEE Trans. Inform. Theory, vol. 38, no. 2, pp. 747–765, Mar. 1992.