Independent Component Analysis of Electrogastrographic Signals

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Abstract. *Electrogastrogram (EGG) is a noninvasive recording of the electrical activity of the stomach. Dominant component of gastric electrical activity called also slow waves originates from the activity of the network of interstitial cells of Cajal located in the gastric wall. The electrogastrographic signal requires longer recording times (usually tens of minutes) due to the low frequency of the slow waves (0.05 Hz). Furthermore, EGG is weaker signal when compared to the other biogenic signals (ECG, respiratory signal). Thus, EGG is usually contaminated by artifacts and other signals, which are sometimes difficult to remove. In the present study, independent component analysis (ICA), as a method for blind source separation, is used for artifact removal and biological signal separation. ICA was applied on 4-channel EGG signal recorded by custom made recording device. Our analysis proves that ICA is able to successfully separate different types of signals (motion artifact, oscillating transients) from the original EGG recordings. We can conclude that ICA could potentially improve further analysis of EGG signal and enhance its interpretation.*

Keywords: biosignal measurement, electrogastrogram, independent component analysis

1. Introduction

Motility is one of basic functional characteristics of the gastrointestinal tract. Recordings of the electrical activity from the gastrointestinal wall surface revealed regular electrical waves (slow waves) that were not directly connected to the contractile activity of the smooth muscles (slow waves were present even if gastrointestinal contraction were absent). Slow waves are, however, the necessary condition for contractions and these waves determine maximal frequency of smooth muscle contractions. Slow waves in the human stomach have frequency 3 cpm (cycles per minute). The origin of the slow waves was controversial for a long time. At present, network of interstitial cells of Cajal (ICC) is believed to generate slow waves [1,2,3,4]. Network of pacemaker ICC is located between neural plexus and layer of the smooth muscle cells in the stomach.

Activity of ICCs can be noninvasively recorded as an electrogastrogram (EGG), which is recorded from electrodes on the surface of the epigastrium. However, in comparison with other biological signals, e.g. cardioelectric or respiratory signal, power of the EGG signal is much weaker. The signal has to be properly filtered and amplified to extract its characteristic features. EGG signal is usually contaminated by other biological signals and artifacts that are difficult to separate by conventional filtering methods.

Recently, a method for blind source separation called independent component analysis (ICA) was introduced by Comon [5]. ICA extracts source signals (independent components) contributing to a mixture of signals (recorded signals) without any knowledge about their properties. This extraction is based on the assumption that component signals are statistically independent, meaning that knowing the properties of one component signal provides no information about the properties of the other signals in the mixture. In the present study we used this method to extract source signals from a set of EGG signals recorded by a custom made EGG device.

2. Methods

EGG measurement

Multichannel measurement of EGG signals with simultaneous recording of one electrocardiogram for heart rhythm monitoring was implemented in the ProGastro 3 device (Fig.1) [6]. It consists of a measuring box with signal amplifiers and a microcomputer-controlled measuring module. The box is

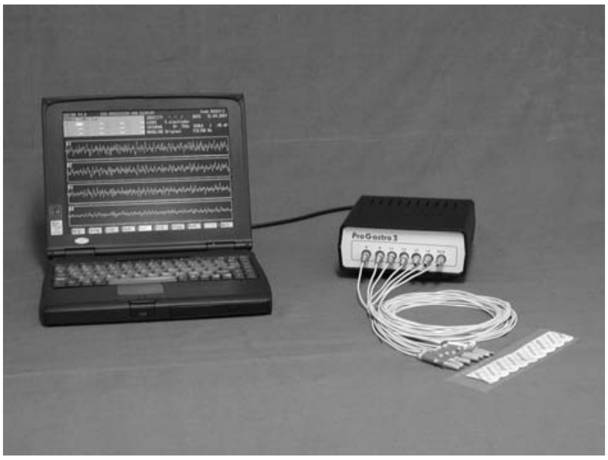

Fig. 1. ProGastro 3 device

connected to a serial port of a notebook computer. Signals are sensed by a set of silver μ-wire subcutaneous electrodes. EGG amplifier with 4 programmable channels, automatic offset compensation, programmable gain 2500 - 20000 and selectable frequency range .015 - .5 Hz or .015 - 3.4 Hz is controlled by ADμC812 8-bit microcontroller. All signals are measured relatively to a single reference electrode, active neutralization electrode ensures common-mode signal rejection ratio higher than 90 dB.

Application software developed in MS Visual C++ and MatLab, is running under Windows 98/2000/XP and allows full control of the measuring box and long term real-time EGG monitoring and recording. Subsequent EGG signal processing includes digital filtering, baseline corrections, interactive amplitude and time interval measurements followed by time-frequency and independent component analysis.

Independent component analysis

Measured data in EGG signals can be modeled as a linear combination of source signals that are non-gaussian and mutually statistically independent by the following equation:

$$\mathbf{x} = \mathbf{A}\ \mathbf{s}$$

where $\mathbf{x} = (x^1, x^2,...,x^n)^T$ is the vector of observed variables, $\mathbf{s} = (s^1, s^2,...,s^n)^T$ is a vector of variables called independent components or source signals, and **A** is a mixing matrix. This equation can be inversed and expressed as follows

$$\mathbf{s} = \mathbf{W}\ \mathbf{x}$$

where the weighting matrix **W** equals the inversed mixing matrix **A**. One independent component can be expressed by the following equation:

$$s = \mathbf{w}^T \mathbf{x} = \sum_j w_j x_j$$

Several algorithms were proposed for computing the independent components and the matrices **A** and **W** [7,8,9]. In the present study, independent components were estimated using FastICA algorithm implemented in MATLAB (available on the web at http://www.cis.hut.fi/projects/ica/fastica/). This software is based on a fixed-point iteration scheme for maximizing non-gaussianity of $\mathbf{w}^T \mathbf{x}$ introduced by Hyvärinen and colleagues [9]. In this algorithm, negentropy (or differential entropy) is a parameter quantifying the amount of mutual information shared by the independent components. Negentropy (J) of a random variable **s** (or of independent components) is the difference between the entropy of a gaussian random variable ($H(s_G)$) and entropy of the random variable s ($H(s)$):

$$J(s) = H(s_G) - H(s)$$

A gaussian random variable has the largest entropy among all random variables of equal variance. Thus, negentropy J(s) is always non-negative and zero if and only if s is gaussian. Maximizing negentropy is therefore equivalent to maximizing nongausianity in a random variable, thus minimizing mutual information. In FastICA algorithm, negentropy is estimated by

$$J(s) \propto [E\{G(s)\} - E\{G(s_G)\}]^2$$

where s is a random variable assumed to be of zero mean and unit variance, s_G is a gaussian random variable of zero mean and unit variance and G is a nonquadratic function [9]. Detailed information on this algorithm can be found in [8,9]

3. Results

The usefulness of ICA for signal separation from a set of EGG signals was analyzed. In Fig. 2, set of recorded EGG signals and 4 independent components separated from these signals are presented.

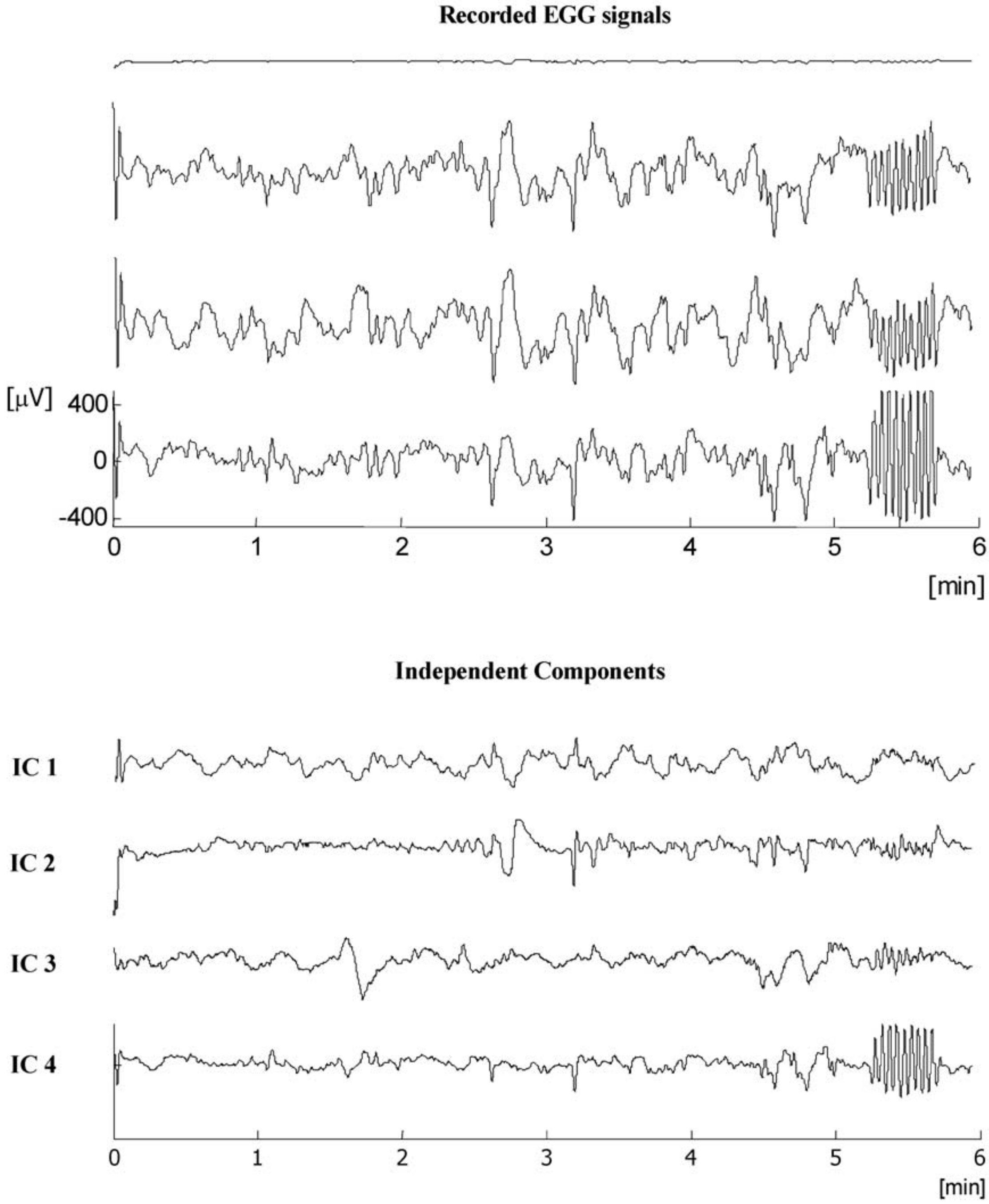

Fig. 2. Set of original EGG signals and set of separated source signals IC1 – IC4 by ICA algorithm.

Recorded signals are contaminated by an artifact at the very beginning of the recorded time period and pronounced in higher frequency signals occurring between the 5^{th} and 6^{th} minute of the recording time interval presented in the figure. ICA application on this set of EGG signals approved potential of this method for artifact removal and signal separation. Artifact was separated as a single independent component IC2 and temporal higher frequency signal occurring in the 6^{th} minute of the EGG recording as component IC4. The first independent component IC1 represents the basic signal originated in stomach with a dominant frequency of 3 cpm.

4. Discussion and Conclusions

Recently, ICA was successfully tested for artifacts removal from EGG signals using the maximal likelihood algorithm [10]. In the present study, usefulness of ICA for artifact removal and signal separation for EGG recordings was tested using fixed-point algorithm proposed by Hyvarinen [9]. ICA is based on the assumption that separated signals are non-gaussian, mutually independent and that the recorded signals are a linear sum of the source signals. It was argued that interesting signals in nature often have non-gaussian distributions (e.g. [11]) and signals with gaussian statistical distribution are thought to be a mixture of non-gaussian ones. It is therefore reasonable to suppose that signal of interest (biological signals and artifacts that should be separated from them) are non-gaussian.

The major constraint of ICA is that it requires at least as many recorded signals as there are source signals in the mixture. EGG recordings contain 4 different signals available for analysis. It is reasonable to suppose that EGG signals are formed by more than only 4 different sources. Iterative optimization is used in fastICA algorithm generated components with a minimum of mutual information. Thus, algorithm generates signals that are not strictly mutually independent but as independent as possible [8]. Independent components could be therefore signals that are the most independent signals comprising the recorded ones.

Common problem of EGG analysis is that there is no direct connection between EGG signal parameter and occurrence of contractions of the stomach. ICA could potentially bring a promising tool for separating signal that could indicate contraction incidence from the signal mixture. We can expect that such a signal is very low in amplitude, has overlapping spectra with other signals and is therefore very difficult for detection by conventional signal analysis methods. ICA is a method that could separate such signals and enables further analysis and detection of hidden signals in the mixed EGG recordings.

Present study approves usefulness of ICA application on EGG signals. The algorithm, used in the study, is suitable for artifacts elimination from the EGG signals. ICA is also useful for separating other biological signals (respiratory signals, electrical activity of the small intestine) from EGG recordings. It improves further analysis of separated signals and their biological interpretation. It could potentially improve also analysis of relations between signals originating from different biological structures.

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