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Removal of Embedded Artefacts in ECG Signals by Independent Component Analysis

Akingbade Kayode Francis and Michael O. Kolawole

Department of Electrical & Electronics Engineering
The Federal University of Technology, Akure, Ondo State, Nigeria

E-mail: + kfakingbade@futa.edu.ng, mokolawole@futa.edu.ng

Abstract: Routinely recorded Electrocardiograms (ECGs) are often corrupted by artefacts; these artefacts make the visual interpretation and analysis of the ECG signal difficult. This paper presents a model, dynamic in structure, sufficiently suitable for removing the ECG artefacts caused by embedded objects in the body using independent component analysis technique. By simulation, the model is able to detect and remove extraneous noises in the conductive paths and discern essential nodes of ECG that are useful to clinicians. Our study, also demonstrates that convolutive ICA can be regarded as a useful tool for accurately estimating the effects of embedded object in the patients on ECG signals.

Key words: Electrocardiograms, artefacts, embedded objects, Independent component analysis, adaptive filtering, electromagnetic waves.

I. Introduction

Routinely recorded electrocardiograms (ECGs) are often corrupted by artefacts; these artefacts make the visual interpretation and analysis of the ECG signal difficult. This recorded signal is vital in diagnosis of a patient's heart activity. Generally, the frequency band of the ECG signal is about 100Hz; typically in the range 0.05 to 100Hz, which includes 50Hz power line noise, baseline wander due to respiration, and muscle induced artefacts resulting from the movement of electrodes during measurement, or other objects that are imbedded in the conductive paths. Power line noise can cause errors by distorting the ECG signal during the measurement of the QRS complex interval or the QT interval, which are important parameters in diagnosis [Lee and Lee, 2005]: an example is when diagnosing arrhythmia or myocardial infarction(Malik and Camm, 1995). Besides the power line noise, other diverse noises can affect measurements including temperature variance of the electric system, static electricity, the patient's potential variance and movement, high-frequency noise, etc. Since the patient's physical condition and the environment can affect this noise, signal processing should be adapted to the environment. The baseline wander [Sahambi et al., 1998]—the below 1Hz low-frequency noise—has the same frequency band as the ST segment of the ECG signal. This component must be removed, or at least identified, to measure the ST segment with precision. Even when noises are removed patient's muscle artefacts are distributed in a wide frequency band, which can generate distortions in the ECG signal. These noises make direct measurement analysis difficult.

This paper presents a technique that detects hidden variables in the conductive path and adaptively filters extraneous noises using modified Independent component analysis (ICA) with least mean square (LMS) filter. ICA is a tool that has been used widely in different fields to separate independent components present in the mixture signals. The applications range from speech processing, brain imaging, and electrical brain signals to telecommunications and stock predictions (Parra and Spence, 2000; Kong et al, 2008; Jung et al, 2000; Davies and Mitianoudis,2003; Bell and Sejnowski, 1995; Makieg et al, 1996).

A distinction is drawn between *blind signal separation* (BSS) and ICA. BSS refers to the entire body of knowledge relevant to blindly separating signals, whereas the term ICA is reserved more specifically for algorithms that perform this separation (Cichocki and Amari, 2002). Separation techniques were named ICA to highlight the fact that independent components were being separated from mixtures of signals (Choi et al, 2002; Amari et. al, 1996).

II. Proposed ICA Model

The proposed ICA model is shown in Fig. 1 and the optimization criterion is in general taken in the least squares family in order to work with linear operations (Bellanger, 1987). By applying the adaptive filter coefficients, the general LMS is capable of removing noise or obtaining a desired signal (Kolawole, 2003).

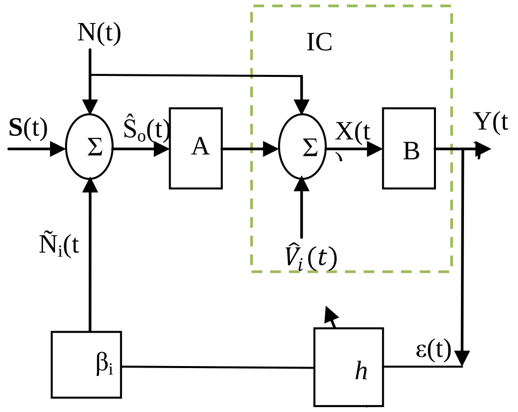

Fig. 1: Proposed adaptive ICA process model

where β_i and *h* are respectively the Adaptive filter weight and the Adaptive algorithm.

Let S be time t indexed, *k*-dimensional independent signals from the linearly mixed observable variables. The ICA model is written as

$$\hat{S}_o(t) = S(t) + N(t) - \hat{N}(t) \tag{1}$$

$$U(t) = A\hat{S}_o(t) \tag{2}$$

$$X(t) = \hat{S}_o(t) + N(t) - \hat{V}(t) \tag{3}$$

$$Y(t) = BX(t) \tag{4}$$

where $\hat{S}_o(t)$, $S(t)$, and $N(t)$, are respectively the optimum independent mixed observed signals, originally mixed unobserved signals, and N(t) is the background noise, which could be due to partial contact of the leads attached to the body, heat (thermal noise from components), power line noise, body induced variant (e.g., baseline wander due to respiration, and muscle artefacts due to movement of electrodes during measurement), etc. A and B are mixing and separating matrices. The optimum noises $\hat{N}(t)$, $\hat{V}(t)$ are defined as

$$\hat{N}(t) = \sum_{i=0}^{L} \beta_i(t) N_{th}(t-i) \tag{5}$$

$$\hat{V}(t) = \sum_{i=0}^{L} \beta_i(t) N_{th}(t-i) = \hat{N}(t) \tag{6}$$

where N_{th} is the acceptable noise threshold, and *L* is the filter order. The proceeding coefficient of the filter can be estimated from the present coefficient and other thresholds:

$$\beta_i(t+1) = \beta_i(t) + 2\eta S(t) N_{th}(t-i) \tag{7}$$

where □ is the convergence constant. It should be noted that the filter order, *L,* might not necessarily be of the same order (or dimension) as that of the independent variables.

The LMS adaptive filter adapts the filter coefficients to achieve desired signal ensuring convergence; that is, minimizing error $\varepsilon(t)$ at each time index:

$$\varepsilon(t) = Y(t) - BX(t) \tag{8}$$

Convergence is slow coming; hence a local minimum is sought leading to establishing threshold values. We noted the difference in change of the filter coefficients as a measure of establishing rate of convergence, specifically

$$\xi_\beta(t) = \sum_{j=0}^{L} \left| \beta_t(j) - \beta_{t-1}(j) \right| \tag{9}$$

If $\xi_\beta(t)$ is large, filter converges to small order. We adjust the filter order to using $\xi_\beta(t) \le \alpha_{th}$ for quick convergence, where α_{th} local minimum threshold. The adaptation gain $G(n)$ is introduced for coefficient updating recursion for the period of the signal measurement:

$$G(n) = \left| \sum_{i=0}^{n} \frac{\hat{S}_o(i)}{S(i) + N(i)} \right| \tag{10}$$

where *n* is the period of the ECG signal for our signals of interest.

Detection of artefacts is achieved by comparing the extraneous noise V(t) (separate from background noise) introduced into the measurement stream. At each time index, the intensity of V(t) is measured relative to the noise threshold level N_{th}. There are no embedded artefacts in the patient's conductive path if

$$\| V_i(t) \| \le N_{th}(t-1), \tag{11}$$

otherwise, artefacts are present, noted and removed. Where $\| V_i(t) \|$ approximates closely to that of $N_{th}(t-1)$, additional filtering is applied ensuring that there no extraneous objects assuming similar profile as background noise.

III. Simulations Results

We used MATLAB R2007b to estimate the performance of the proposed model with dynamic filter. We generate ECG signals containing PQRS-T nodes similar to healthy person's ECG signal without noise, as shown in Fig 2. Non-zero mean Gaussian noise was then superimposed on the source signal and in the measurement stream. Typical waveform is shown in Fig 3. The output signal obtained from ICA algorithm; after the artefacts components have been removed is seen in Figure 4. The essential nodes of ECG that clinicians are looking for are easily discernable from Fig 4 than that in Fig 3 in which the information had been buried in the artefacts.

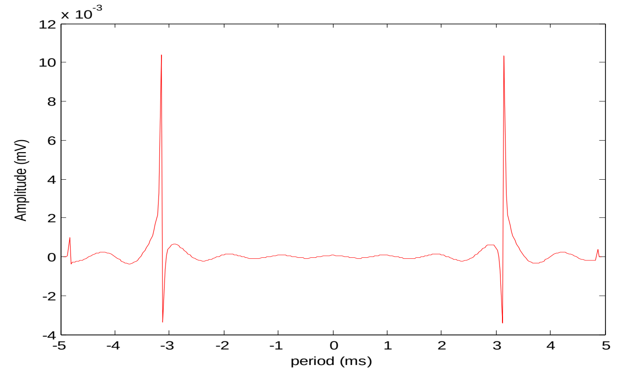

Figure 2: ECG source signal

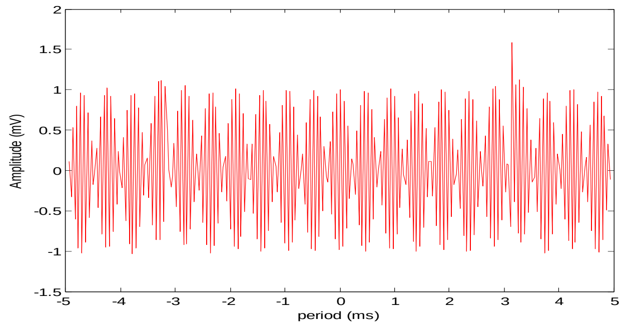

Figure 3. Corrupted ECG signal with the introduction of artefacts

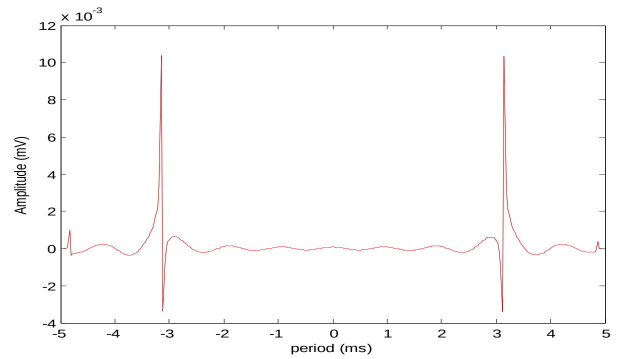

Figure 4. Recovered ECG signal after the artefacts have been detected and filtered.

IV. Conclusion

The proposed ICA model has demonstrated that artefacts in the conductive paths can be isolated and filtered to provide discernable nodes that clinicians look for. Work is still continuing to finetune the parameters so that clinical trials can start. The model shows that convolutive ICA can be regarded not only as a mathematical generalization of an instantaneous model, but also as a more powerful tool for accurately estimating the effects of embedded object in the patients on ECG signals.

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