

# Motion Artifact removal in Ambulatory ECG Signal using ICA

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**Abstract**— In recent years Ambulatory ECG signal recording and monitoring becoming a popular using wearable AECG monitor and patient can do his daily routine life for real time detection of the events of cardiac arrest and timely treatment of cardiac disorder. But ambulatory ECG signals is contaminated by many artifacts among major artifact is motion artifact due to physical body movement so it must be removed before proper clinical analysis of AECG. In this paper we used offline ECG data of Physionet (MIT-BIH arrhythmia database) as well as we have recorded AECG signal using self made AECG recorder (Wearable device) as well as from Biopac MP36 data acquisition system with lead II configuration. Here four types of physical movement data taken like right hand movement, sitting to stand movement, waist and walking movement with faster and slower pace of five healthy person. We have identified motion artifact offline synthesis ECG data as well as of different four physical activities from AECG signal using Independent Component Analysis (ICA), it is an efficient blind source separation technique used by many researcher worldwide.

**Keywords**- AECG, Physical activity (PA), Motion artifact, Wearable device (WD), Independent Component Analysis (ICA), FastICA

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## I. Introduction

ECG is one of the best recognized biomedical signals for diagnostic of cardiac disorder. Most of the cardiovascular disease is identified from ECG signal analysis that is a simplest, noninvasive, cost effective and oldest method of cardiac investigation. In recent years Ambulatory ECG signal recording and monitoring becoming a popular using wearable AECG recorder and patient can do his daily routine life for real time detection of the events of cardiac arrest and timely treatment of cardiac disorder. A Signal generated by the heart and monitored by the AECG monitor are weak and includes many artifacts. The origin and nature of these artifacts are of considerable interest, particularly for long term monitoring applications. Some of the artifacts are caused due to physiological reasons like electromyograph (EMG or muscular activity) noise and slow baseline wandering due to respiration. There are some artifacts which are due to non physiological reasons, for example, 50 Hz power line interference and motion artifacts in ECG. Electrode Contact Noise where the electrodes are not tightly coupled to the patient causing some distortion, loose electrodes and broken leads may produce a variety of artifacts that may stimulate arrhythmias, Q waves, or inverted T waves. An instrumentation noise is generated by electronic devices also interfere with ECG signal. An Electrosurgical Unit, where high-frequency signals from the Electrosurgical Unit, used by surgeons during operation interfere with the ECG signal. The presence such kind of the artifacts will make any morphology based diagnosis difficult [1, 2].

In ambulatory monitoring skin stretching due to body or limb movement or physical activity (PA) is a main cause of motion artifacts in AECG signals. The motion artifact induced due PA has a spectral overlap with ECG signal in 1-10 Hz [2]. Many important cardiac features of ECG signal

like P and T wave has significant energy content in this overlapping band of 1-10Hz. So it is very difficult to separate or eliminate motion artifact completely without affecting these cardiac features in AECG [2]. Therefore researchers have developed various techniques to removal of motion artifact from AECG signal. The motion artifact induced due to the PA as shown in fig. 1 is an Ambulatory ECG signal. Here in figure R wave identified but difficult to identify Q and T wave especially of cardiac patient, so cardiac diagnosis becomes difficult so motion artifact poses a major challenge in the long term cardiac monitoring using a wearable AECG monitor. Thus the recorded ECG signal is not just the cardiac signal but a composite ECG signal containing motion artifacts. In other words, the composite ECG signal is superposition of two independent events: the cardiac signal and the motion artifact signal induced due to the body movement activity (BMA). Since the W-ECG recorder performs amplification, filtering and digitization of the acquired electrical signal from the electrodes, an additive random noise arising out of the device electronics may be present in the digitized ECG signal. This signal is referred as sensor noise. Therefore, the ambulatory ECG signal  $r(n)$  in digital form can be modeled as sample wise addition of three different signal components

$$r(n) = q(n) + s(n) + \alpha(n) \quad \dots(1)$$

Where  $q(n)$ ,  $s(n)$  and  $\alpha(n)$  are samples of cardiac signal, motion artifact signal and sensor noise, respectively. Since the dc bias has been removed, it is assumed that the noise component have zero mean. The care has been taken to keep the sensor noise has much less power level than the other signal components in the AECG signal,  $r(n)$ . The mathematical model in (1) used for representing the AECG has been proposed in [3-4].

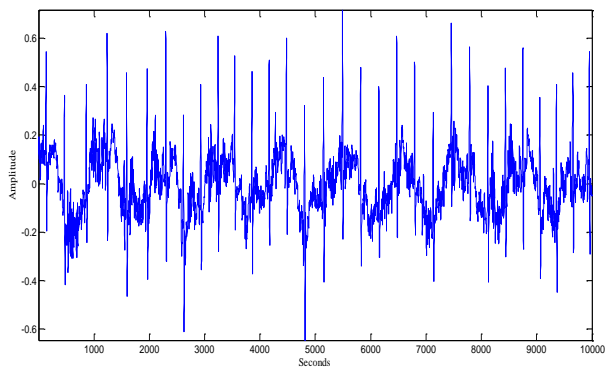


Fig.1 AECG signal with left arm movement .The R peaks are visible indicating the presence of heart beats but the other ECG features like P and T waves are contaminated severely due to the motion artifact.

There are various methods used for AECG signal analysis and identification of motion artifact, like wavelet based methods are extensively used in pre-processing, denoising and analysis of ECG signals, adaptive filter based methods used for ECG signal processing and to remove motion artifact, neural networks also used for detection of events and pattern classifications in AECG signal analysis, the AECG is analyzed beat-by-beat using a recursive principal component analysis (RPCA) based method in [2].etc.

In this paper Independent Component Analysis (ICA), it is an efficient blind source separation technique used for identification and removal of motion artifact of offline synthesis ECG data of Physionet (MIT-BIH arrhythmia database) as well as AECG signal for different types of physical movement. Here we recorded AECG signal of five people of four types of physical activity using AECG recorder at sample frequency of 500 Hz for a period of 60 second at slower and faster pace. For a physical activity like continuous hand movement, waist movement, seat to stand movement and walking movement at slow and faster pace.

## II. Ambulatory ECG data acquisition

There are many Wearable AECG recorders available in market. We used self made Wearable ECG recorder that is customized, light weight, compact, battery operated, low power dissipation, low cost device and a person can easily carry with him in a wearable clothes. It can record ECG in digital format at various sampling rate. It consist wireless transceiver, microcontroller on board with software for ECG recording as shown in fig. 2. We also used biopac MP36 system for recording AECG signal. The biopac MP36 System is a data acquisition system with built-in universal amplifiers that can record a wide range of physiological signals as shown in fig. 3.

AECG parameter can be displayed on Laptop or PC using LABVIEW software and also it can store in PC. Here AECG recorded for different type of physical activity. We have performed four type of body movement activity of healthy person and recorded AECG for (1) Right arm movement (2) ) Sitting up and down from standstill (3) Twisting of waist and (4) Walking for short duration with slow and faster pace of five healthy.

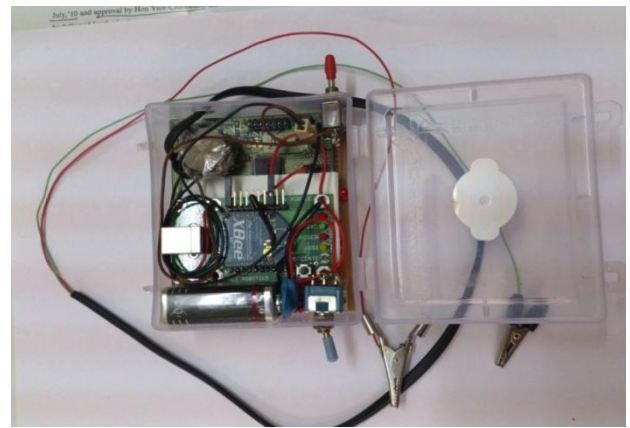


Fig. 2 AECG monitor for ECG recording



Fig. 3 Biopac MP36 data acquisition system with lead II configuration.

## III. ICA method

In [8] suggested a general model for ICA is that the sources are generated through a linear basis transformation, where additive noise can be present. Suppose we have N statistically independent signals,  $s_i(t)$ ,  $i = 1, \dots, N$ . We assume that the sources themselves cannot be directly observed and that each signal,  $s_i(t)$ , is a realization of some fixed probability distribution at each time point t. Also, suppose we observe these signals using N sensors, then we obtain a set of N observation signals  $x_i(t)$ ,  $i = 1, \dots, N$  that are mixtures of the sources. A fundamental aspect of the mixing process is that the sensors must be spatially separated so that each sensor records a different mixture of the sources. With this spatial separation assumption in mind, we can model the mixing process with matrix multiplication as follows:

$$x(t) = A.s(t) \quad \dots \dots \dots (1)$$

Where A is an unknown matrix called the mixing matrix and  $x(t)$ ,  $s(t)$  are the two vectors representing the observed signals and source signals respectively. Incidentally, the justification for the description of this signal processing technique as blind is that we have no information on the mixing matrix, or even on the sources themselves. The objective is to recover the original signals,  $s_i(t)$ , from only the observed vector  $x_i(t)$ . We obtain estimates for the sources by first obtaining the “unmixing matrix” W, where,

$W = A^{-1}$ . This enables an estimate,  $\hat{s}(t)$ , of the independent sources to be obtained:

$$\hat{s}(t) = W \cdot x(t) \quad \dots\dots\dots (2)$$

The diagram in Fig. 4 illustrates both the mixing and unmixing process involved in BSS. The independent sources are mixed by the matrix A (which is unknown in this case). We seek to obtain a vector y that approximates s by estimating the unmixing matrix W. If the estimate of the unmixing matrix is accurate, we obtain a good approximation of the sources. The above described ICA model is the simple model since it ignores all noise components and any time delay in the recordings.

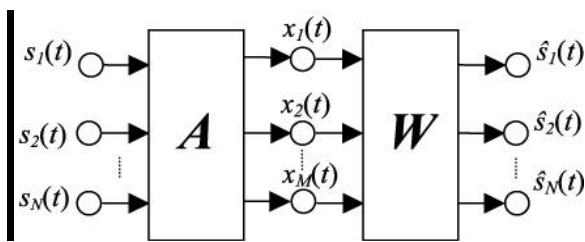


Fig. 4 Blind source separation (BSS) block diagram.  $S_i(t)$  are the sources.  $X_i(t)$  are the recordings,  $\hat{S}_i(t)$  are the estimated sources A is mixing matrix and W is un-mixing matrix [9].

There are several ICA algorithms available in literature. However the following three algorithms are widely used in numerous signal processing applications. These include FastICA, JADE, and Infomax. Each algorithm used a different approach to solve equation. FastICA is a fixed point ICA algorithm that employs higher order statistics for the recovery of independent sources. FastICA can estimate ICs one by one (deflation approach) or simultaneously (symmetric approach). FastICA uses simple estimates of Negentropy based on the maximum entropy principle, which requires the use of appropriate nonlinearities for the learning rule of the neural network. One of the important conditions of ICA is that the number of sensors should be equal to the number of sources. Unfortunately, the real source separation problem does not always satisfy this constraint. This section focuses on ICA source separation problem under different conditions where the number of sources is not equal to the number of recordings.

Here first we have used the first ECG signals available from Physionet (MIT-BIH arrhythmia database). A data set text file number 100,101,102,102,104,200,201,202,203 and 205 used for offline ICA analysis. The additive motion artifacts are synthesized for offline ICA analysis. We have use 10 ECG data set on which slow and fast low frequency signal is mixed for ICA analysis and using FastICA algorithm we successfully separated synthesized as well as we also find ECG beat number, synthesis motion interval. Here we first Here we recorded an AECG signal in lead II configuration that is filtered and smoothen using a moving average low pass filter in span for the moving average of 201 of four physical movements of five people at slow and faster pace. In ICA two source signals required for that we derived filter signal using low pass butter filter and use as second source signal fig. 7 (a) and 7 (b) of hand movement. The

independent components are then mixed according using an arbitrarily chosen mixing matrix A as shown in fig.7 (c) and 7 (d); finally, the mixtures are separated using FastICA algorithm out of various algorithm discussed in literature review to obtain motion artifact and motion artifact removed signal, shown in fig.7 (e) and 7 (f).

#### IV. Results

Using Independent component analysis we identified and detected and separated motion artifact and clean ECG signal of offline synthesis ECG data of Physionet (MIT-BIH arrhythmia database) as well as recorded AECG signal of four physical activities of five people. As shown in fig. 5 and fig. 6 are result of derived motion artifact of synthesis data and four physical activities like slow hand movement in fig. 7 while fig. 8 of fast hand movement similar way we removed motion artifact of waist movement, walking movement and eat to stand movement for 60 second duration of physical movement continuously. Here table 1 and table 2 is results off offline ECG data of Physionet (MIT-BIH arrhythmia database) while table 3 and 4 is of AECG signal ICA analysis. Here fig. 7(a) shows original recorded AECG signal on which identified motion artifact used as first source signal. Fig. 7(b) is filtered signal used as second source signal, while fig. 7(c) and (d) are mixed signal and using Fast ICA we separated two independent component they are clean ECG signal and motion artifact signal as shown in fig. 7(e) and (f). In below results we also visualize the number of peak motion interval is increase in faster movement as compared to slower movement and ECG beats.

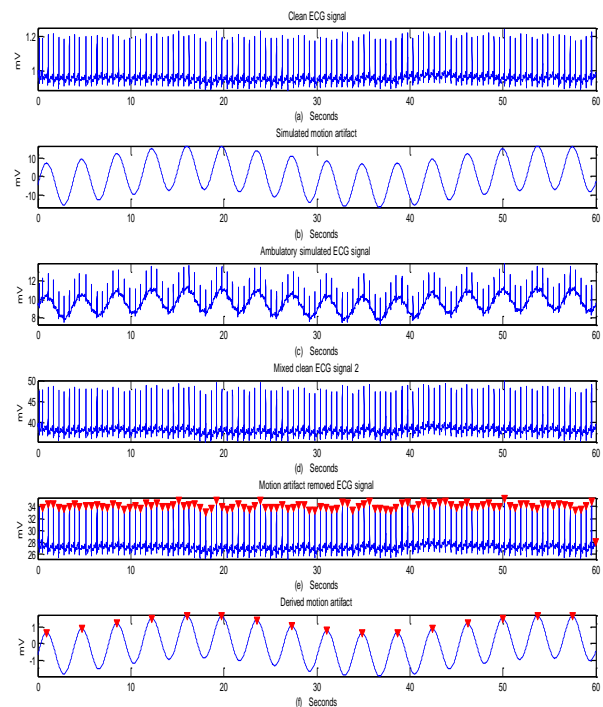


Fig. 5 ICA analysis of 100.txt for slow synthesis signal

Table 1 slower synthesis movement

Sr. No.	File #	Average Peak Interval	No. of peak	No. of ECG beat
1	100.txt	4677	7	103
2	101.txt	4743	6	97
3	102.txt	4743	6	101
4	103.txt	4739	6	99
5	104.txt	4732	6	102
6	200.txt	1833	16	110
7	201.txt	1885	16	104
8	202.txt	1884	16	74
9	203.txt	1885	16	85
10	205.txt	1885	16	124

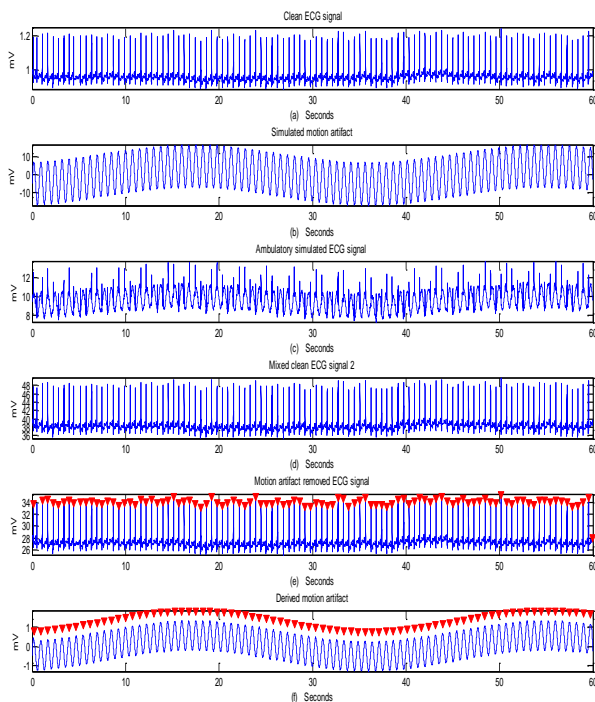


Fig. 6 ICA analysis of 100.txt for fast synthesis signal

Table 2 faster synthesis movement

Sr. No.	File #	Average Peak Interval	No. of peak	No. of ECG beat
1	100.txt	471	64	103
2	101.txt	471	64	97
3	102.txt	471	64	101
4	103.txt	471	63	98
5	104.txt	471	63	103
6	200.txt	376	79	110
7	201.txt	376	80	104
8	202.txt	376	79	74
9	203.txt	377	79	84
10	205.txt	376	80	124

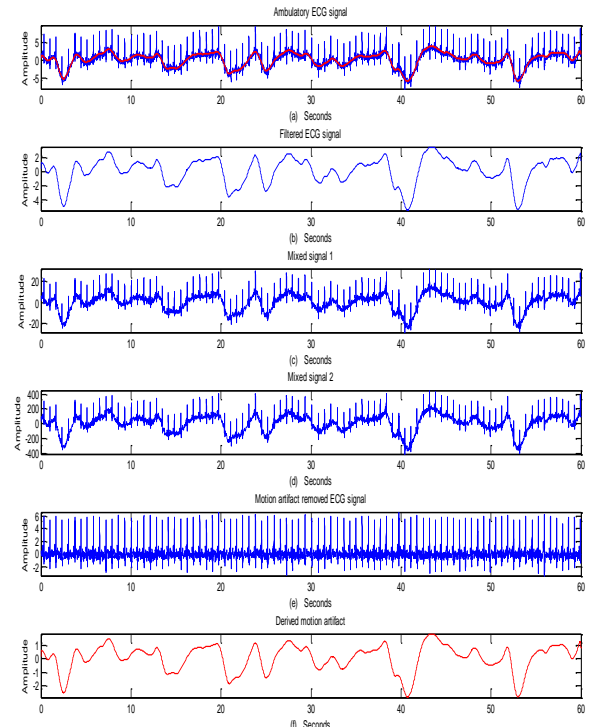


Fig. 7 Slow hand movement

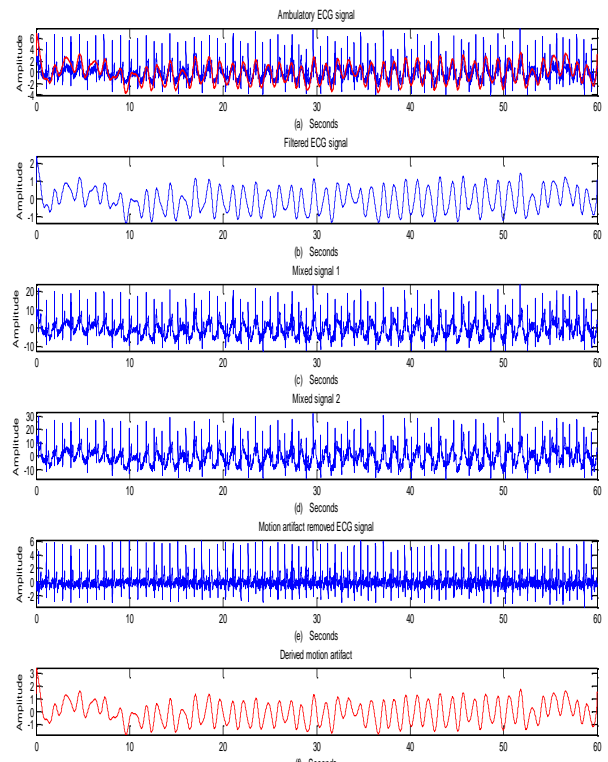


Fig. 8 Fast hand movement

## V. Conclusion and discussion

In this chapter Independent Component Analysis (ICA), it is novel blind source separation technique used for identification and removal of motion artifact of offline synthesis ECG data of Physionet (MIT-BIH arrhythmia database) as well as AECG signal for different types of physical movement. Here we recorded AECG signal of five people of four types of physical activity using AECG



recorder at sample frequency of 500 Hz for a period of 60 second at slower and faster pace. For a physical activity like continuous hand movement, waist movement, seat to stand movement and walking movement at slow and faster pace.

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