Electrocardiogram beat detection enhancement using Independent Component Analysis

Jakub Kuzilek and Lenka Lhotska

Department of Cybernetics, Faculty of Electrical Engineering, CTU in Prague, Prague, Czech Republic, contact e-mail: kuziljak@fel.cvut.cz

Abstract

Beat detection is a basic and fundamental step in electrocardiogram (ECG) processing. In many ECG applications strong artefacts from biological or technical sources could appear and cause distortion of ECG signals. Beat detection algorithm desired property is to avoid these distortions and detect beats in any situation. Our developed method is an extension of Christov’s beat detection algorithm, which detects beat using combined adaptive threshold on transformed ECG signal (complex lead). Our offline extension adds estimation of independent components of measured signal into the transformation of ECG creating a signal called complex component, which enhances ECG activity and enables beat detection in presence of strong noises. This makes the beat detection algorithm much more robust in cases of unpredictable noise appearances, typical for holter ECGs and telemedicine applications of ECG. We compared our algorithm with the performance of our implementation of the Christov’s and Hamilton’s beat detection algorithm.

Keywords: Beat detection, Independent Component Analysis, ECG, Noise reduction.
1. Introduction

Beat detection is the most fundamental task in electrocardiography, the positions of QRS or ventricular beats serve as a basis for further analysis of electrocardiogram (ECG). It is for example the most crucial task in heart rate variability (HRV) analysis, which analyses RR interval changes during long periods of time in order to detect heart disorders. The necessity of correct detection arises with each application of QRS detection algorithms. Many researchers proposed large variety of methods for solving this task [1, 2, 3, 4, 5]. The most commonly used in real world applications are Pan-Tompkins QRS detection algorithm [3] and its modification introduced by Hamilton and Tompkins [6] or Christov’s beat detection algorithm [4].

Pan-Tompkins and its modification Hamilton-Tompkins algorithms are based on patient-specific detection threshold. Algorithms work on single lead ECG, which is modified by set of preprocessing digital filters in order to enhance positions of QRS complexes. Pan-Tomkins algorithm has higher accuracy for various beat morphologies and it outperforms methods developed earlier. On the other hand Hamilton-Tompkins algorithm has been used for HRV analysis in various applications.

More recently, Christov released his beat detection algorithm, which is based on combined adaptive threshold and transformation of multidimensional ECG signal into single complex lead data. The complex lead transformation is more robust in presence of noise corrupting useful ECG and the algorithm is more stable.

In many applications strong artefacts from biological or technical sources could appear and cause distortion of ECG signals. Many algorithms for beat
detection perform much worse in that case. Christov’s detection algorithm deals with noise that accompanies the ECG by transforming the ECG signal to signal called complex lead, which enhances position of QRS complex and reduces effect of common artefacts presented in ECG. But this algorithm has its limits, too. We try to improve its performance by transforming ECG signal to components using Independent Component Analysis (ICA) [7, 8, 9], which is the method for estimation of “independent” elements in data.

ICA represents one solution of Blind Source Separation (BSS) problem, which is the extraction of the set of signals based merely on their mixtures. The BSS/ICA methods try to estimate components that would be as independent as possible and their linear combination is original data. Estimation is done by an iterative algorithm, which maximizes function of independence, non-iterative algorithm, which is based on joint diagonalization of correlation matrices, or recursive algorithm. In many ICA algorithms it is assumed that data is centred and whitened.

For the last decade ICA methods have been employed in variety of biomedical applications. Most works use only limited number of ICA algorithms such as SOBI [10], FastICA [9] or JADE [11]. In addition, separation performance of electro-physiological sources is still unknown. Due to this uncertainty a single best method for biomedical area cannot be selected [12]. At present only few problems in ECG have been solved by ICA due to limited interest of researchers in ECG applications. First problem, on which ICA was applied, was artefact and noise removal [13, 14, 15, 5]. Next ICA application area in ECG processing is extraction of fetal ECG (fECG) from records obtained by electrodes placed on mother body [16, 17]. Another application is extraction
of atrial activity for atrial flutter analysis [18, 19]. Previous papers represent main-stream research in ECG applications of ICA, but there are several other papers presenting other applications [20, 21].

For beat detection ICA is used only in few paper mostly as a part of filtering step [5, 22]. On the other hand Principal Component Analysis (PCA), which is the ”half” of ICA [7], is used more often [5, 23, 24, 25]. In [23] PCA is used for ECG dimensionality reduction as a part of preprocessing step of the algorithm. Other papers [5, 24, 25] present methods, which are insufficiently described and thus cannot be implemented in our study.

In our study we used JADE [11], which is from the family of joint diagonalization based ICA algorithms. It works with fourth order cross-cumulant tensor in order to obtain best solution for BSS problem.

Our offline algorithm successfully combines ICA method JADE with Christov’s beat detection algorithm creating a signal called complex component, on which beats were detected using combined adaptive threshold. The transformation to complex component is similar to transformation to the complex lead, but it introduces one more step - independent components estimation and selection of ECG activity. Thus the algorithm works properly in presence of strong artefacts and noises.

2. Data and methods

2.1. Data

In our experiments we used data freely available on MIT medical storage Physionet [26]. We used two databases:
• MIT-BIH Arrhythmia database [27] - contains 48 half-hour two channel ambulatory ECG recordings digitized at 360 samples per second with 11-bit resolution over 10 mV range annotated by two or more cardiologist.

• Normal Sinus Rhythm database [26] - contains 18 long-term two channel ECG recordings of subjects with no significant arrhythmias digitized at 128 samples per seconds per channel with 12-bit resolution over 10 mV range.

2.2. Simulated noise

According to [1] we can expect various kinds of noise presented in ECG. The most common ones are:

• Power line interference - consists of 50 Hz (60 Hz in U.S.) pickup and its harmonics, typical amplitude is up to 50 percent of peak-to-peak ECG amplitude

• motion artifacts - transient baseline changes caused by changes in electrode-skin impedance, the cause of impedance change is the slow motion of electrode on the body surface, typical amplitude is up to 500 percent of peak-to-peak ECG amplitude

• muscle contraction - generates artefactual millivolt-level potentials, its standard deviation is around 10 percent of peak-to-peak ECG amplitude

• baseline drift and ECG amplitude modulation with respiration - is represented as slow sinusoidal component at respiration frequency, its am-
plitude variation is 15 percent of peak-to-peak ECG amplitude and typical frequencies at 0.15 Hz to 3 Hz.

In addition to these four noises we observed noise typically generated by electrode cable movement during holter recording of ECG. This noise has large amplitudes up to 200 percent of peak-to-peak ECG amplitudes and typical power spectra with peaks at 1.5, 3.16, 6.3 and 8 Hz.

In order to test performance of the algorithm we artificially added noises to ECG recordings. The noises were artificially generated as follows:

- Electromyographic noise - is simulated as random Gaussian signal with deviation around 10 percent of peak-to-peak ECG amplitude

- Power line interference - 50 Hz sinusoid with amplitude 0.333 mV

- Baseline wander - slow sinusoid (0.333 Hz) with the amplitude around 1 mV

- Electrode cable movement - generated as sum of sinusoids with different amplitudes and frequencies ranging from 0.1 to 1 mV and 1.5 to 8 Hz

Each type of simulated noise is added to ECG at four different levels: 25, 50, 75, 100 percent of the maximum amplitude. The noise is added to each lead of ECG with different amplitude estimated from ECG amplitude. The examples of generated noises are shown in Fig. 1.
2.3. Christov’s beat detection algorithm

The Christov’s beat detection algorithm is based on complex lead transform, which is defined as follows:

\[ X[n] = \frac{1}{L} \sum_{j=1}^{L} |x_j(n+1) - x_j(n-1)|, \] (1)

where \( X[n] \) is \( n^{th} \) sample of signal calculated by complex lead transform, \( L \) is number of measured ECG leads, \( x_j(n) \) is \( n^{th} \) sample from \( j^{th} \) lead. The transformation can be seen as average difference calculated from all leads. Example of calculated complex lead is shown in Fig. 2.

After the calculation of complex lead Christov employed combined adaptive threshold to find peaks, which correspond to beat positions. The combined adaptive threshold is calculated as sum of three thresholds:

- Threshold \( M \) (adaptive steep-slope threshold) - reflects the amplitude of currently detected beats
• Threshold $F$ (adaptive integrating threshold) - reflects the presence of high frequency noise in data and increases the combined threshold in that case

• Threshold $R$ (adaptive beat expectation threshold) - intended to deal with heartbeats of normal amplitude followed by beats with very small amplitude

![Figure 2: Complex Lead (down) estimated from ECG (top) with combined adaptive threshold MFR](image)

The algorithm can work in two modes, namely real-time and pseudo-real-time, which performs back search in case of no detection for long time. The algorithm is then pushed back to last detected beat and starts search with lowered combined adaptive threshold.

2.4. Independent Component Analysis

Independent Component Analysis represents solution for the extraction of the set of signals based merely on their mixtures. ICA assumes linear
combination of sources (called components):

\[ X = AS, \]

where \( X \) is a mixture of source signals, \( A \) is the mixing matrix that characterizes environment through which source signals pass, and \( S \) are the source signals.

In many ICA algorithms it is assumed that the data vector \( x \) has zero mean (centred) and its correlation matrix has the form \( E\{xx^T\} = I \) (whitened).

ICA has two disadvantages:

- We cannot specify order of components (the order of rows in matrix \( S \) and columns in matrix \( A \) could be randomly changed without any effect on the result)

- We cannot estimate energy of components (we have no apriori information about matrices \( A \) and \( S \) - multiplication of random row with scalar value in matrix \( S \) and division of competent column in matrix \( A \) with the same value leads to random change of amplitude of components)

2.5. **JADE algorithm**

**JADE** [11] is an extension of **FOBI** [28]. Both of them work with pre-whitened data \( z \):

\[ z = Vx = VAs, \]

where \( z \) is whitened data, \( V \) is whitening matrix, \( x \) are mixed signals, \( A \) is mixing matrix and \( s \) are desired source signals.

Now for **FOBI** algorithm consider matrix:

\[ \Omega = E\{zz^T||z||^2\}, \]
where $z$ are pre-whitened data. Assuming data pre-whitened by ICA model it follows:

$$
\Omega = E\{VAss^T(VA)^T||VAs||^2\} = W^T E\{ss^T||s||^2\} W,
$$

(5)

where $VA$ is orthogonal and $W = (VA)^T$ is mixing matrix. Using independence and unit variance (it does not affect independence property of signals) of $s_i$ matrix $\Omega$ stands for:

$$
\Omega = W \text{diag}(E\{s_i^2||s||^2\}) W = ... = W \text{diag}(E\{s_i^4\} + n - 1) W
$$

(6)

Last equation shows that matrix $W$ can be obtained by eigenvalue decomposition of matrix $\Omega$, which is decomposed to diagonal matrix consisting of the fourth order cumulants of $s_i$ and to orthogonal matrix $W$. This algorithm is the most efficient algorithm for ICA computation. $FOBI$ has restriction, under which it works, namely all ICs have different kurtosis - so applicability of the method depends on particular data.

The $JADE$ is the extension of $FOBI$, it takes several matrices $\Omega$ forming the fourth-order-cross-cumulant tensor [7]:

$$
F(M) = E\{(z^T M z z z^T)\} - 2M - tr(M) I,
$$

(7)

where $M$ is eigenmatrix of cumulant, $z$ are whitened data, $I$ is unit matrix and $tr(M)$ is trace of matrix defined as:

$$
tr(M) = \sum_i m_{ii}.
$$

(8)

Using (7) whitened correlation matrices can be defined alternatively as:

$$
\Omega = F(I) = E\{||z||^2 z z^T\} - (n + 2) I.
$$

(9)
Thus we can take a matrix $M$ and replace matrix $I$ in FOBI algorithm. This matrix would have a linear combinations of cumulants of independent components as its eigenvalues. Now we take more than one matrix, jointly diagonalize them and find the best result.

For diagonalization of cumulant matrices several algorithms have been developed. The one used in the original JADE algorithm is based on Givens rotations [11]. But it can be replaced with more efficient ones - QAJD [29] and its extension FAJD [30] based on off-diagonal elements minimalization, LLAJD [31] based on Hadamards inequality, QRJ2D/LUJ2D [32] based on QR or LU decomposition or the latest one UWEDGE [33] based on weighting of criteria based on minimalization of off-diagonal elements.

2.6. Algorithm

The main idea, which lies behind our algorithm is the question - can we enhance ECG activity before ECG is transformed into complex lead? The algorithm, which enhances the activity, should have extract ECG from unknown mixture of ECG and other signals (power line interference, breathing, etc.) and pass this extracted sources into the complex lead transform.

The problem formulation contains the answer: use method for solving BSS such as ICA to enhance ECG activity. The algorithm is then easily derived from preceding one - instead of using the ECG use selected components obtained by JADE algorithm and these components transform into complex component (similar to complex lead). JADE preserves overall spatial distribution of ECG activity and separates it from other activities. The algorithm work flowchart is shown in Algorithm 1. The change in Christov’s algorithm is hidden in the method for estimation of complex lead - it is replaced with
method for estimation of complex component.

**Algorithm 1 Algorithm**

**Input:** ECG signal

1: Estimate complex component
2: Initialize thresholds \((M, F, R)\) and their buffers
3: for all samples of complex component do
4: Update weights \((M, F, R)\)
5: if current sample \(> (M + F + R)\) (beat detected) then
6: Update thresholds buffers and thresholds
7: Store detected beat position
8: else if beat is not detected for longer than twice average RR interval then
9: Start detection again from last detected beat with lowered threshold
10: end if
11: end for

**Output:** Beat positions

As we mentioned above complex component method first estimates independent components in data using JADE algorithm described in Section 2.5. Next it decides, which components contain ECG activity, and finally estimates the complex component signal from these selected components using Equation 1.

JADE is data driven transformation, thus we never know, in which order and with which scale we obtain the estimated components. In order to make the algorithm fully automatic, one needs to create a robust decision system for detection of ECG activity.
Our decision algorithm is based on the observation that ECG has super-Gaussian distribution \([12, 5, 14]\), thus the values of its kurtosis are larger than values of other presented signals (e.g., EMG is nearly Gaussian with kurtosis close to zero). So the decision algorithm calculates kurtosis of each component, sorts them according to their absolute values and chooses \(n\) components with sum of their kurtosis larger than 75\% of sum of all kurtosis values.

These components are then combined using complex lead transformation (Eq. 1) and returned to the main method, which works similar to Christov’s original algorithm. The overview of the complex component method is shown in Algorithm 2.

\[
\textbf{Algorithm 2 Algorithm}
\]

**Input:** ECG signal

1: Pre-process input signal (Remove mean; Filter power line interference and muscle artefacts)
2: Estimate components using \textit{JADE} algorithm
3: Calculate kurtosis of components
4: Normalize values of kurtosis with maximal kurtosis calculated
5: Sort descending normalized values of kurtosis and permute components accordingly to sorting of their normalized kurtosis
6: Select first \(n\) components whose sum \(\geq\) threshold
7: Calculate complex component from \(n\) selected components
8: Post-process complex component (Filter noise magnified by complex lead transformation)

**Output:** Complex component
2.7. Evaluation method

For evaluation we used standard statistical indices Sensitivity ($Se$), Positive predictivity ($P^+$) and F-measure ($F$), which are derived from three parameters:

- Correctly detected beats (True positives=TP)
- Falsely detected beats (False positives=FP)
- Undetected beats (False negatives=FN)

Sensitivity is the parameter describing how many beats are correctly detected. Thus its value is calculated using this equation:

$$Se = \frac{TP}{TP + FN}.$$  \hspace{1cm} (10)

Positive predictivity characterizes the algorithm in sense of the false detection of beats. Its value is estimated as follows:

$$P^+ = \frac{TP}{TP + FP}.$$  \hspace{1cm} (11)

The F-measure statistics is defined as harmonic mean of Sensitivity and Positive predictivity:

$$F = 2 \frac{Se \times P^+}{Se + P^+}.$$  \hspace{1cm} (12)

All statistical indices ranges from 0 % (worst) to 100 % (best). The values over 95 % are considered as good results.
3. Results

Figures 3 and 5 show summarized results of our algorithm, Hamilton’s algorithm and Christov’s algorithm. Each figure shows the evolution of F-measure according to the percentage of noise amplitude added to signals. For more details see Appendix A.

3.1. Results on MIT/BIH Arrhythmia Database

Figure 3 shows summarized results on MIT/BIH Arrhythmia Database. The first observation shows that the Hamilton’s algorithm performance is strongly dependent on the noise presence and its power. This is due to the algorithm nature - it uses differentiation in preprocessing step, which magnifies differences caused by noise. Hamilton’s algorithm performance in presence of base line wander is stable. This is due to the simulation of this noise using slowly changing sinus function. The high-pass filtering reduces the slow sinus noise efficiently and enables the detection to perform similarly in all cases.

On the other hand the Christov’s algorithm performance is more robust against the presence of common noises, this is due to the filtering of standard frequencies containing these typical noises during preprocessing step. But this algorithm fails in presence of non-standard noises. The presence of non-standard noises is typical for holter ECG and telemedicine applications, which are by their nature more affected by wide range of noises. The Christov’s algorithm performance is then very easily affected by their presence. This can be observed on Fig. 3d, where non-standard noise was added to original data. Very interesting is the decrease of F-measure, when the
base line wander artefact occur (Fig. 3b). We examined the results and the algorithm does not use and high-pass filter for slow artefacts suppression and suppression during differentiation in complex lead transformation insufficiently removes base line wander. It reduces its amplitude, but the artefact is still presented in resulting complex lead signal.

Our algorithm was designed to increase stability and robustness of Christov’s algorithm in presence of unpredictable events (artefacts). This goal has been achieved - the only one noise, where our algorithm ”fails” is base line wander, but this artefact can be reduced using filtered input. The failure was examined and it is due to the statistical nature of JADE algorithm. It failed to estimate slow sinus as one component and divided it into more components. One of these components has larger kurtosis (two orders by magnitude above) than ECG activity. The detection of such component will be our next work. See Figure 4 for examples of good estimation base line wander component, ECG activity component and bad estimation of base line wander component.

Our algorithm is very successful in presence of noise, which mimics the QRS complex activity in frequency domain (electrode cable movement artefacts). Its stability is caused by extraction of ECG activity during computation of complex component signal, which is the basis for QRS complex detection.

3.2. Results on Normal Sinus Rhythm Database

Figure 5 shows summarized results on MIT Normal Sinus Rhythm Database. We can observe, again, that Hamilton’s algorithm decreases its performance with higher noise powers presented in ECG. One of the interesting obser-
Hamilton’s algorithm in such a case outperforms the Christov’s beat detection algorithm. This shows us, that Hamilton’s algorithm is designed more independently on data and it performs much better in presence of unpredictable events than Christov’s algorithm, which is designed to deal with common noise events efficiently. Again we can observe that Christov’s algorithm has difficulties with base line wander.

Figure 3: Summarized values of F-measure for the developed algorithm and different types of artefacts on MIT/BIH Arrhythmia Database
Our algorithm works similar to the performance on the MIT/BIH Arrhythmia Database with only one exception. We observed that its performance in case of base line wander is much more stable. We can assume that the event of ”wrong” estimation of components does not appear in our experiments with this database.

4. Conclusion

We have developed an extension of the well-known Christov’s beat detection algorithm, which enables dealing with ECG signal highly corrupted by artefacts. Our method introduces JADE algorithm into the complex lead estimation step separating the ECG activity outside the other uninteresting activities, which can be considered as noises in case of beat detection. The JADE algorithm estimated independent components in sense of 4th order statistics. From these components we were able to select those containing
ECG activity only with one exception, which is the extraction of activity in presence of simulated base line wander using slow sinus wave. The selection of these components will be our next step in development of our algorithm.

Algorithm properties were tested on standard databases (MIT/BIH Arrhythmia Database and MIT Normal Sinus Rhythm Database) and its properties were compared to Christov’s like beat detection algorithm and Hamilton’s like detection algorithm. Tests were performed using simulated noises - power line interference, base line wander, EMG and electrode cable move-
ment. First three noises are common types presented in recorded data and the last one is uncommon one. We decided to add this, because we are dealing with holter ECG recordings and these data contains many unpredictable noise events, which are not usual at all.

Our enhanced version of Christov’s beat detection algorithm performs much more stable in presence of noise and it outperformed Christov’s and Hamilton’s like algorithms, which are designed for the typical cases of resting ECGs.

The computational complexity of our algorithm is increased only by computational complexity of JADE algorithm, which is one of the fastest BSS algorithms. So the benefit of ECG activity estimation is much greater than loss of computational time. The amount of space required for data storing is also slightly increased - JADE algorithm stores several matrices with cumulants and the amount of data stored is dependent on number of ECG leads.

Acknowledgment

Research described in the paper has been supported by the CTU Grant SGS10/279/OHK3/3T/13 and the research program No. MSM 6840770012 "Transdisciplinary Research in Biomedical Engineering II" of the CTU in Prague.

Appendix A. Detailed results

Tables A.1 and A.2 show detailed results visualised in graphs plotted on Fig. 5 and Fig. 4.
Again we can observe the same results as in graphs. Our method proves to be more robust to noises than other beat detection methods with one exception - the base line wander artefact, when the estimation of components converge to solution with divided sinus wave into several components with kurtosis higher than standard ECG activity.

<table>
<thead>
<tr>
<th>Noise type</th>
<th>F-measure [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Christov’s algorithm + ICA</td>
</tr>
<tr>
<td>Clear signal</td>
<td>99.06</td>
</tr>
<tr>
<td>Power Line Interference</td>
<td>99.05 99.05 99.04 99.03</td>
</tr>
<tr>
<td>EMG</td>
<td>98.19 97.10 96.69 96.93</td>
</tr>
<tr>
<td>Base Line Wander</td>
<td>95.78 95.27 95.06 95.00</td>
</tr>
<tr>
<td>Electrode Cabele Movement</td>
<td>99.19 99.24 99.25 99.25</td>
</tr>
</tbody>
</table>

Table A.1: Detailed results on MIT/BIH Arrhythmia Database
Table A.2: Detailed results on Normal Sinus Rhythm Database

<table>
<thead>
<tr>
<th>Noise type</th>
<th>F-measure [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Christov’s algorithm + ICA</td>
</tr>
<tr>
<td>Clear signal</td>
<td>98.68</td>
</tr>
<tr>
<td>Noise type</td>
<td></td>
</tr>
<tr>
<td>Noise level [%]</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>98.68</td>
</tr>
<tr>
<td>50</td>
<td></td>
</tr>
<tr>
<td>75</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td></td>
</tr>
<tr>
<td>Power Line Interference</td>
<td>98.68</td>
</tr>
<tr>
<td>EMG</td>
<td>98.67</td>
</tr>
<tr>
<td>Base Line Wander</td>
<td>98.61</td>
</tr>
<tr>
<td>Electrode Cabele Movement</td>
<td>98.75</td>
</tr>
</tbody>
</table>

Appendix B. Declarations

- Competing Interests: None declared

- Funding of research:
  - CTU Grant SGS10/279/OHK3/3T/13
  - Research program No. MSM 6840770012 ”Transdisciplinary Research in Biomedical Engineering II” of the CTU in Prague

- Ethical Approval: Not required

References


[17] J. F. Cardoso, Fetal electrocardiogram extraction by source subspace


[23] B. Huang, Y. Wang, QRS Complexes Detection by Using the Principal Component Analysis and the Combined Wavelet Entropy for 12-Lead...


[29] R. Vollgraf, K. Obermayer, Quadratic optimization for simultaneous


