Independent Component Analysis Methods to Improve Electrocardiogram Patterns Recognition in the Presence of Non-Trivial Artifacts

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***Abstract*—Electrocardiogram (ECG) signals are affected by various kinds of noise and artifacts that may impede correct recognition by automated monitoring or diagnosis systems. Independent component analysis (ICA) is considered as a new technique suitable for the separation and removal of diverse noises independent of ECG signals. This paper first proposes the application of independent component analysis to ECG signal pre-processing and then compares the performances of two major types of ICAs namely Infomax and Fast ICAs in ECG signal de-noising. The annotated benchmark samples from MIT-BIH arrhythmia database are used for experiments. We compare the signal to noise ratio improvements in the real ECG data with different ICA algorithms and the recognition rates. It is found that both types of ICA can effectively improve the ECG recognition in the presence of non-trivial artifacts, but FastICA slightly outperforms. However, it is worth mentioning that the Infomax algorithm might be further optimized.**

***Index Terms*—electrocardiogram, independent component analysis, machine learning, pattern recognition.**

I. Introduction

Electrocardiogram (ECG) is a common clinical diagnostic tool and its use has extended to long-term and on-site monitoring of many cardiac conditions and diseases. Prompt diagnosis, timely treatment and long term monitoring can prevent unexpected heart attack or other forms of heart failure. Automated ECG analysis is a typical signal processing and pattern recognition system studied and used clinically over the past few decades. It is known noisy signals due to unreliable contact of electrodes, body motion and interferences from other bio-signals impede correct recognition of clinically significant conditions, mitigating the reliability of these automated systems.

For example, sometimes, ECG monitoring is needed outside the clinical environment in a first aid setting. Due to motion of anxious patients and associated artifacts found in ECG signals are severer than those taken in hospitals or other clinical settings. Round the clock ECG (Holster) monitoring, ambulatory ECG, and sports ECG are all prone to high levels of motion induced noise. These ECGs are often taken over a prolonged period, which justifies the need of automated analysis. De-noising or noise separation becomes particularly important in these applications. On the other hand, heartbeat is not the only source of signals that are picked up by contact electrodes; ECG is often contaminated by other bioelectrical signals. The non-homogeneity between the ECG and noises suggests that they are independent to a great extent. Independent component analysis (ICA) based blind source separation (BSS) is considered in this study to obtain clean ECG signals in the presence of non-trivial artifacts from ECG leads.

Independent component analysis [1]–[4] which is a form of blind source separation method is a statistical signal processing technique used for separating a set of signals into mutually independent component signals.

Noise and artifact removal is the first step for ECG signal processing [5] used ICA for removing breathing artifact with promising results which led them to apply ICA technique for more noise separation. [6] presented their work by using well established MIT-BIT noise stress database it proposed ICA based architecture for BSS separation of linearly mixed signals. The architecture consisted of a high-pass filter, a two-layer network based on ICA algorithm and a self-adaptive step-size. Which was derived from the mean behaviour of output signals. The two layered algorithm provided fast convergence as compared to other algorithms which used

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whitening technique along with ICA algorithm. Independent component analysis can be implemented with different algorithms each have its own merits, as they can be problem specific. For the case of noise and artifact removal from ECG [7] , performed comparative study of different ICA algorithms for ECG signal processing. Some motion artifact are ectopic in nature hance theycannot be easily detected by conventional filters [8] used PCA-ICA based algorithms for motion artifact removal. Carrying the idea forward [9] used two lead design for motion artifact removal along with feature extraction of ECG using ICA , which was extension to previous work.

The adoption of (ICA) for ECG signal processing has been attempted for different purposes by several authors: ICA/BSS was used to acquire extra information about the heart and body [10]; Hidden factors of biomedical signals were extracted using ICA and BSS [11]–[14]; Motion induced artifacts were removed from ECG [9].

This paper first presents the principle and methods of applying the ICA to ECG artifacts removal, and then compares the performances of two mainstream ICA algorithms namely Infomax and Fast ICAs.

II. ECG Noise and Artifact Model

The ECG is a record of electrical activity generated by heart beats and measured from the surface of the body using special electrodes. It can be viewed, in a simpler term, as an electrical signature of heart behavior. ECG signals are acquired by placing electrodes on the body surface at different prescribed locations and connecting the electrodes in different configurations to differential voltage amplifiers and a recorder. Three-lead ECG recording methods is the most common of all. It is based on Einthoven triangle [15]. Three leads are used to measure heart electrical activities,

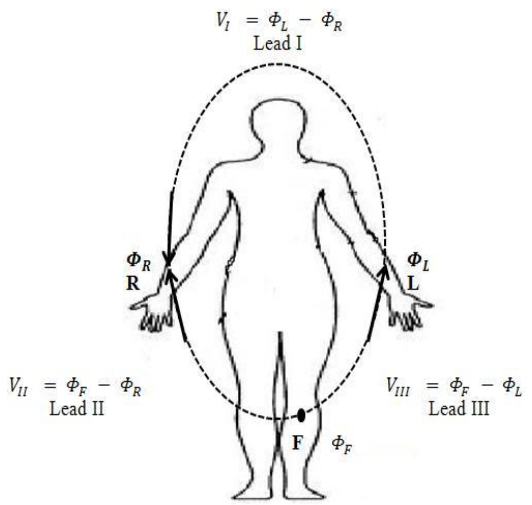

Figure 1. Einthoven triangle and ECG limb leads definition

The Einthoven limb leads (1) are defined in the standard way as:

$$Lead\ I: \quad V_I = \Phi_L - \Phi_R$$
$$Lead\ II: \quad V_{II} = \Phi_F - \Phi_R \qquad (1)$$
$$Lead\ III: \quad V_{III} = \Phi_F - \Phi_L$$

where Φ refers to measured potential from the electrodes at related locations. According to Kirchhoff's law, these lead voltages have the following relationship:

$$V_I + V_{III} = V_{II} \qquad (2)$$

Therefore, only two of these three leads are independent. Lead II data from the MIT-BIH data set was used for this study.

Due to the body movement, ECG signals often get contaminated with motion induced artifact known as 'em' which are difficult to be removed by conventional filtering because of their ectopic nature. An extra electrode on body may transform the signal artifact removal problem into an independent component analysis one: The recording of ECG lead II is the linear combination of the pure ECG and the lumped noise N, while the signal from the extra electrode is a different linear combination of the ECG and N [9]. If the ECG and the N are statistically independent, the ICA can thus be used to separate them out.

III. ICA Algorithms

A. From Cocktail Party Problem to ICA and BSS

Independent component analysis is a statistical method to identify underlying factors or components that are statistically independent. It is also viewed as a single layer unsupervised artificial neural network. ICA algorithms are known to be effective in solving blind source separation problems.

The cocktail party problem in audio can be a classic illustration of the ICA for blind source separation. The objective is to separate the individual voices of speakers from samples of mixture of spoken voices recorded by the microphones.

$$x_1(t) = a_{11}\, s_1(t) + a_{12}\, s_2(t) \qquad (3)$$
$$x_2(t) = a_{21}\, s_1(t) + a_{22} s_2(t) \qquad (4)$$

where x_1 and x_2 are the sound signals received by the microphones, s_1 and s_2 are two speaking sources, coefficients a's represent attenuation due to transmission distances. We aim to separate individual speaker voice from the voice mixture, with no information about the sources available. The objective is to find a de-mixing matrix $\boldsymbol{W}$ so that we can get a source signal separated from

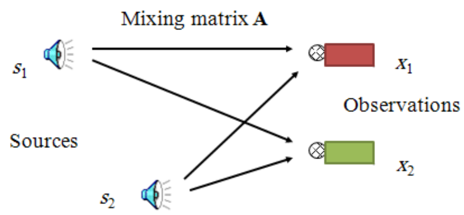

Figure 2. Cocktail Party Problem

$$\boldsymbol{s}(t) = \boldsymbol{W}\boldsymbol{x}(t) \qquad (5)$$

where $\boldsymbol{S}(t)$ and $\boldsymbol{X}(t)$ are source and received signal vectors. This is based on the condition and assumption that signals are non-Gaussian and statistical independent.

It is postulated that parasitic noise or artifacts found in ECG signals are statistically independent of the ECG itself. It is also assumed that all noise sources can be treated as a single lumped source; therefore ICA may be applied to separate out the artifacts from actual ECG signals. The lack of precise models of parasitic artifacts in ECG and unpredictable nature of them mean that these assumptions may not be strictly proven but can indication of how these artifacts can be removed and why the ICA can be a solution. Empirical investigations via observing improved signal to noise ratios and recognition rates indirectly validate these assumptions, and thus prove the usefulness of the methods.

B. Infomax ICA and FastICA

The methods used to find the de-mixing differentiate the ICA algorithms. Infomax ICA and FastICA are popular ones successfully used for many similar applications. Infomax attempts separate signals through minimizing Shannon mutual information or maximizing entropy in outputs via unsupervised learning. The algorithm is often deemed as a single layered unsupervised neural network and was previously applied to speech separation problems by Bell and Sejnowski [16].

The learning objective of such ICA neural networks is to minimize the mutual information between the outputs as illustrated in Fig. 2

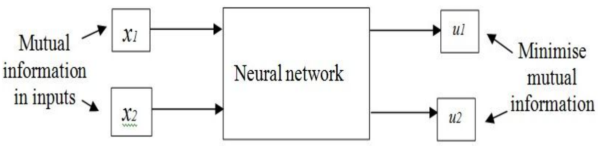

Figure 3. Learning objective of ICA neural networks

Two independent sources, s1 and s2, are linearly mixed by arbitrary coefficients a11, a12, a21, and a22 to give the mixture x1 and x2 according to Equations 3 and 4. When written in a matrix format

$$\boldsymbol{x}(t) = A\boldsymbol{s}(t) \tag{6}$$

where the input vector $S = [s_{1,}s_2]^T$, the mixture vector $X = [x_{1,}x_2]^T$and the mixing matrix $\boldsymbol{A}$ is

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \tag{7}$$

and A is non-singular.

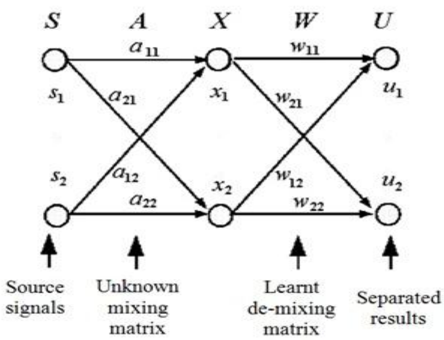

Figure 4. Mixing and de-mixing model

The ICA is to find a de-mixing matrix $\boldsymbol{W}$ as shown in the right half of Fig. 6, so that $u1$ and $u2$, which are recovered versions of *s1* and *s2*, and can be obtained by

$$U = WX \tag{8}$$

where the de-mixing matrix is

$$W = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} \tag{9}$$

And the recovered vector is

$$\mathrm{U}= [u1, u2]^{\ T} \tag{10}$$

This is achieved by minimising mutual information found in *u1* and *u2* using an unsupervised neural network with only one linear summation layer as depicted in Fig. 6 (right half). The two neurons have linear summation basis functions but may have different types of activation functions. The following activation function proposed by [17], was used as a starting point. The activation might be further tailored and optimized for this application but this is beyond the scope of this paper.

$$f(z) = \Big[\frac{1}{2}z^5 + \frac{2}{7}z^7 + \frac{15}{2}z^9 + \frac{2}{15}z^{11} - \frac{112}{3}z^{13} + 128z^{15} - \frac{512}{3}z^{17}\Big] \tag{11}$$

where z is used to represent the summed input signals being sent to the activation function. The training follows weight updating formula.

$$W(n+1) = W(n) + \alpha\big[I - f\big(U(n)\big)U^T(n)\big]W^{-T}(n) \tag{12}$$

where η is the step size.

FastICA developed in [18] is another possible algorithm for independent component analysis. It uses maximum non-Gaussianity as a criterion of statistical independence and the algorithm is based on the central limit theorem. FastICA is a fixed point ICA algorithm that employs higher order statistics for the recovery of independent sources and can estimate independent components one by one or simultaneously (symmetric approach). FastICA uses simple estimates of Negentropy based on the maximum entropy principle to measure non-Gaussianity. This can be described as:

$$J(x) = H_G(x) - H(x) \tag{13}$$

where x is a random vector known to be non-Gaussian, $H\ (x\ )$ is the entropy and $H_G(x)$ Is the entropy of a Gaussian random vector whose covariance matrix is equal to that of (x). For a given covariance matrix, the distribution that has the highest entropy is the Gaussian distribution. Negentropy is thus a strictly positive measure of non-Gaussianity. In [19] some modifications were proposed to the above methods for calculation of negentropy

$$J(V) = E\big(_{\emptyset}(V)\big) - E\big(_{\emptyset}(U)\big)^2 \tag{14}$$

where V is a standardized non-Gaussian random variable (zero mean and unit variance), U a standardized Gaussian random variable and $\emptyset\,(.)$ a non-quadratic function (generally Tanh (.)). After some modifications FastICA algorithm can be explained in these steps:

1) Let i = 0,initialize the weight vector: w = w(0)

2) Increment *i; i = i + 1*
3) Adjust w $w(i+1) = E\{zg(w_i^T z)\} - E\{zg'(w_i^T z)\}\, w_i$
4) Normalize $w(i+1) = \frac{w(i+1)}{\|w(i+1)=\|}$
5) If convergence is not achieved return to step 3

After getting convergence find independent component $y_1 = \mathrm{wZ}$, where Z $= z_1, z_2, z_3 \ldots z_n$ is whitened signal matrix and Y = $y_1, y_2, y_3 \ldots y_n$ are estimated independent components.

IV. Methods

An annotated and validated database is important for the study of ECG signal processing and pattern recognition in general, and such a "standard" database is particularly useful in this study. This allows for the validation of the newly developed algorithms and the comparison with the results from other works. We have selected the MIT-BIH database because it is completely annotated by medical specialists and arguably the most popular one used by many other authors and quoted in numerous important publications in this field e.g [10], [14], [20], [21]. The associated noise recordings in the dataset were made using physically active volunteers. Standard ECG recorders, leads, and electrodes were used; the electrodes were placed on the limbs in positions where the subjects' ECGs were virtually invisible, giving real samples of non ECG bioelectrical signals from subjects. Electrode motion artifact is generally considered the most troublesome, since it can mimic the appearance of ectopic beats and cannot be removed easily by simple filters, as can noise of other types [22]. The so called 'em' noise dataset was also obtained from MIT-BIH Noise Stress Test Data base. 'em' artifact was mixed with pure ECG with various SNR for more extensive testing of our approach. The equation for mixing two signals can be given as

$$\begin{aligned} Modified\ Lead\ II &= S1 + N' \\ Limb\ Electrode &= S2 + N'' \end{aligned} \tag{15}$$

where modified lead II records ECG signal and part of noise, the limb electrode also picks up ECG signals and noise but ECG is weaker in this sensing location, so majority of limb electrode signal is composed of 'em' noise.

FastICA and Infomax algorithm were used to separate the pure ECG and noise artifacts. After the separation of pure ECG and motion related artifacts, we classified the ECG segments into normal and abnormal ones in order to compare with the results from classification performed on noisy ECG. Classification was done using Back Propagation neural network (BPNN) implemented using MATLAB software. Artificial Neural Networks (ANNs) -propagation neural network used in this study which is are widely used classifier for ECGs [11], [20], [21], [24]–[26]. Backa three-layer feed-forward structure [27]. The first layer is the input layer that has the ICA features as inputs. The second layer, also called the hidden layer, has 20 neurons and the output layer has two neurons, which is same as the types of ECGs to be classified.

In this study, the hyperbolic tangent functions are used in the first and second layers, and the identity function is used in the output layer. The weight and bias values in the BPNN are updated by Levenberg-Marquardt optimization method [20] with a learning rate of 0.1. A criterion of 0.01 in mean-square-error is empirically determined to terminate the iterations in the training phase of the classifier.

V. Results

The MIT-BIH database of annotated real subject and patient ECG and noise samples, it is possible to mix the ECG and noise with known signal to noise ratios and then identify the effectiveness of ICA as a de-noising pre-processor for the ANN based pattern recognition system. Table I should the percentage of correct recognition with and without ICAs.

TABLE I. Comparison of Classification Accuracy of Different ICA Algorithms

Noise (dB)	*-12*	*-6*	*0.1*	*6*	*12*	*24*
Accuracy (Infomax, %)	76.7	86.7	87.3	92.4	95.1	96.1
Accuracy (FastICA, %)	83.3	87.1	88.2	93.5	96.4	98.7
Accuracy Without ICA (%)	58.3	60.1	81.6	82.9	90.7	97.1

The results indicate that to achieve a greater than 80% accuracy, using ANN patten recognition, a higher than 0 dB signal to noise ratio is typically required. In the presence of non-trivial artifacts, the ICAs, both the Informax one and the FastICA, can effectively clean noisy signals and provide a virtual increase of signal to noise ratio up to 12 dB. This is evidenced by that fact that as a signal to noise ratio of -12 dB ICA can improve the recognition rate to 83.3%, which is similar to the performance ANN (only) at a signal to noise ratio of 0dB. Fig. 3 illustrates the waveforms of the signals before and after cleaning.

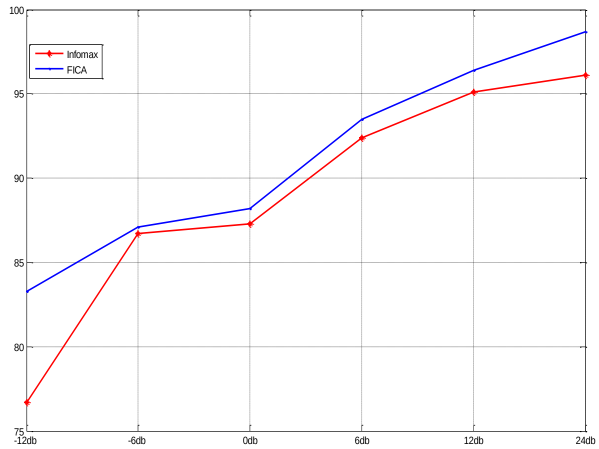

Figure 5. Comparison of the accuracy of the different ICA algorithm when applied to ECG data contaminated by noise artifacts

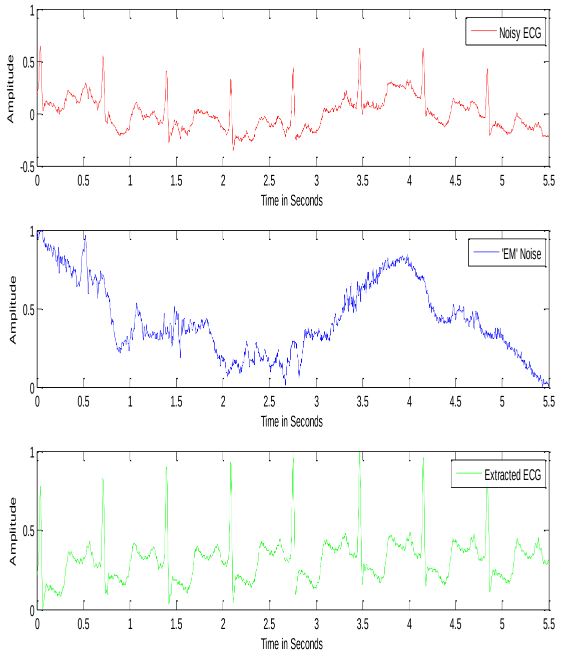

Figure 6. ECG contaminated with noise, S/N=-06db (Top Panel), 'EM' Noise (Mid Panel), ICA cleaned ECG (Bottom Panel), Y Axis are normalized after ICA.

VI. CONCLUDING REMARKS

From the results presented in this paper, it is apparent that ICA can effectively separate and remove noise independent of cardiac activities, in particular motion induced artifacts in ECG signals, thus improving automatic ECG recognition, The proposed method has potential application to the pre-processing of ECG signals with non trivial noise and other artifacts independent of ECG, commonly seen in diverse application scenarios such as sports ECG, and Holster monitoring. Even though the data set used in this study concerns mainly motion induced artefacts, the fact that these data are real bioelectrical signal samples taken from subjects rather than simulated data from models means that the dataset per se contain all other non ECG bioelectrical interferences typically found in ECG leads. The significantly improve performance of recognition after ICA based signal cleaning seems to suggest the ICA is also effective in cleaning interferences other than motion induced and contact noise. This is not surprising, as these non-ECG components found in leads, signals are most likely to be statistically independent from those of ECGs.

Amongst several ICA algorithms, two most established ones, namely Infomax ICA and FastICA were experimented with. The focus has been placed on signal cleaning performance. It has been revealed that FastICA outperformed in almost all aspects investigated. However, it is worth mentioning the kernel function used in the Infomax algorithm might be optimized, which remains in the future work of this study. It is also observed that in better signal to noise conditions (24 dB) Informax ICA can degrade recognition accuracy by 1%. The likely cause of this is the distortion that the ICA algorithm imposed on its outputs.

This work proposes and validated a new method to eliminate artifacts found in ECG signals using independent component analysis based blind source separation. Validation testing of artificial neural networks trained on raw data and ICA-processed data clearly show the effectiveness of ICA as a de-noise pre-processing for motion artifacts elimination, offering up to 30% of the classification successful rate or 12 dB virtual signals to noise ratio increase in adverse signal to noise ratio conditions. FastICA outperforms Infomax ICA in this application.

REFERENCES

[1] A. Hyvärinen, J. Karhunen, and E. Oja, "What is independent component analysis?" *Independent Component Analysis*, pp. 145–164, 2001.

[2] A. Hyvärinen and E. Oja, "Independent component analysis: Algorithms and applications," *Neural Networks*, vol. 13, no. 4, pp. 411–430, 2000.

[3] G. R. Naik and D. K. Kumar, "An overview of independent component analysis and its applications," *Informatica: An International Journal of Computing and Informatics*, vol. 35, no. 1, pp. 63–81, 2011.

[4] M. I. Owis, A.-B. Youssef, and Y. M. Kadah, "Characterisation of electrocardiogram signals based on blind source separation," *Medical and Biological Engineering and Computing*, vol. 40, no. 5, pp. 557–564, 2002.

[5] J. O. Wisbeck, A. K. Barros, A. K. B. Yy, and R. G. Ojeda. (1998). Application of ICA in the separation of breathing artifacts in ECG signals. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.40.3057

[6] A. K. Barros, A. Mansour, and N. Ohnishi, "Removing artifacts from electrocardiographic signals using independent components analysis," *Neurocomputing*, vol. 22, no. 1, pp. 173–186, 1998.

[7] M. Sarfraz, F. Li, and M. Javed, "A comparative study of ICA algorithms for ECG signal processing," 2011, pp. 135–138.

[8] I. Romero, "PCA and ICA applied to noise reduction in multi-lead ECG," in *Proc. Computing in Cardiology*, 2011, pp. 613–616.

[9] M. Sarfraz and F. Li, "Independent component analysis for motion artifacts removal from electrocardiogram," *Global Perspectives on Artificial Intelligence*, vol. 1, no. 4, 2013.

[10] M. I. Owis, A.-B. Youssef, and Y. M. Kadah, "Characterisation of electrocardiogram signals based on blind source separation," *Medical and Biological Engineering and Computing*, vol. 40, no. 5, pp. 557–564, 2002.

[11] K.-T. Chou and S.-N. Yu, "Categorizing heartbeats by independent component analysis and support vector machines," in *Proc. Eighth International Conference on Intelligent Systems Design and Applications*, vol. 1, 2008, pp. 599–602.

[12] C. J. James and C. W. Hesse, "Independent component analysis for biomedical signals," *Physiological Measurement*, vol. 26, no. 1, p. R15, 2005.

[13] T. M. Nazmy, H. El-Messiry, and B. Al-Bokhity. (2010). Adaptive neuro-fuzzy inference system for classification of ECG signals. [Online]. pp. 1–6. Available: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.208.1102

[14] S.-N. Yu and K.-T. Chou, "A switchable scheme for ECG beat classification based on independent component analysis," *Expert Systems with Applications*, vol. 33, no. 4, pp. 824–829, 2007.

[15] J. Malmivuo and R. Plonsey, *Bioelectromagnetism: Principles and Applications of Bioelectric and Biomagnetic Fields*, Oxford University Press, 1995.

[16] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural Computation*, vol. 7, no. 6, pp. 1129–1159, 1995.

[17] H. Madhuranath and S. Haykin, "Improved activation functions for blind separation: Details of algebraic derivations," CRL Internal Report No, 1998.
[18] A. Hyvärinen, "The fixed-point algorithm and maximum likelihood estimation for independent component analysis," *Neural Processing Letters*, vol. 10, no. 1, pp. 1–5, 1999.
[19] A. Hyvärinen, J. Karhunen, and E. Oja, *Independent Component Analysis*, vol. 46, John Wiley & Sons, 2004.
[20] X. Jiang, L. Zhang, Q. Zhao, and S. Albayrak, "ECG arrhythmias recognition system based on independent component analysis feature extraction," in *Proc. TENCON 2006. IEEE Region 10 Conference*, 2006, pp. 1–4.
[21] N. Belgacem, M. A. Chikh, and F. B. Reguig, "Supervised classification of ECG using neural networks," 2003.
[22] G. B. Moody, R. G. Mark, and A. L. Goldberger, "PhysioNet: A web-based resource for the study of physiologic signals," *Engineering in Medicine and Biology Magazine, IEEE*, vol. 20, no. 3, pp. 70–75, 2001.
[23] J.-S. Wang, W.-C. Chiang, Y.-T. C. Yang, and Y.-L. Hsu, "An effective ECG arrhythmia classification algorithm," in *Bio-Inspired Computing and Applications*, Springer, 2012, pp. 545–550.
[24] O. Castillo, P. Melin, E. Ramírez, and J. Soria, "Hybrid intelligent system for cardiac arrhythmia classification with fuzzy k-nearest neighbors and neural networks combined with a fuzzy system," *Expert Systems with Applications*, vol. 39, no. 3, pp. 2947–2955, 2012.
[25] M. A. Chikh, N. Belgacem, A. Chikh, and F. Bereksi-Reguig, "Application of neural nets to detect Artrial Premature Beat (APB)," 2003.
[26] A. S. Al-Fahoum and I. Howitt, "Combined wavelet transformation and radial basis neural networks for classifying life-threatening cardiac arrhythmias," *Medical & Biological Engineering & Computing*, vol. 37, no. 5, pp. 566–573, 1999.
[27] J.-S. R. Jang, C.-T. Sun, and E. Mizutani, "Neuro-fuzzy and soft computing-a computational approach to learning and machine intelligence [Book Review]," *IEEE Transactions on Automatic Control*, vol. 42, no. 10, pp. 1482–1484, 1997.

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