Performance Comparison of Known ICA Algorithms to a Wavelet-ICA Merger

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Abstract

These signals are however contaminated with artifacts which must be removed to have pure EEG signals. These artifacts can be removed by Independent Component Analysis (ICA). In this paper we studied the performance of three ICA algorithms (FastICA, JADE, and Radical) as well as our newly developed ICA technique. Comparing these ICA algorithms, it is observed that our new techniques perform as well as these algorithms at denoising EEG signals.

Keywords: Independent Component Analysis, Wavelet Transform, Unscented Kalman Filter, Electroencephalogram

1. INTRODUCTION

The use of Electroencephalogram in the field of Medicine has had a great impact on the study of the human brain. The signals received have several origins however that lead to the complexity of their identification. This complexity is made of both the pure EEG signal and other non-cerebral signals called artifacts or noise. The artifacts have resulted in the contamination of the EEG signals, hence the removal of these artifacts has generated a large number of denoising techniques.

One method has been Independent Component Analysis (ICA) originating from the field of Blind Source Separation [5]. This technique calls for the separation of the EEG into its constituent independent components (ICs) and then eliminating the ICs that are believed to contribute to the artifact sources. It is subjective, inconvenient and a time consuming process when dealing with large amount of EEG data. Another method employed is wavelet transformation. This technique calls for the decomposition of the EEG signals into wavelets and artifacts removal done using thresholding and shrinkage.

Each of the above techniques presents their own limitations. In our opinion a combination of the two should produce a more effective technique. This is possible as each technique is used to overcome the limitation of the other. We present in this paper therefore a new method of extracting artifacts from EEG signals – Cycle Spinning Wavelet Transform ICA (CTICA). CTICA is compared to other known ICA algorithms, and saving useful EEG data.

2. SUPPORTING LITERATURE

2.1 EEG Signals

The language of communication with the nervous system is electric so when the neurons of the human brain process information, they do so by changing the flow of electrical currents across their membranes. These changing currents generate electric and magnetic fields that can be recorded from the surface of the scalp. The electric fields are measured by attaching small electrodes to the scalp. The potentials between different electrodes are then amplified and recorded as the electroencephalogram; (EEG), which means the writing out of the electrical activity of the brain (that which is inside the head). EEG recordings therefore, show the overall activity of the millions of neurons in the brain.

There are five basic wave types, measured in Hertz (HZ), found in EEG signals (Tab. 1). The most prominent type is the alpha rhythm recorded mainly over the posterior regions of the scalp close to the places in the brain that process visual information. When the eyes are open the alpha rhythm is very small and when the eyes are closed it becomes large.

Type	Frequency(Hz)	Normally
Delta (δ)	0.5-4 Hz	Deep, dreamless sleep, non-REM sleep, unconscious
Theta (θ)	4 – 8 Hz	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha (α)	8 – 13 Hz	Relaxed, but not drowsy, tranquil, conscious
Beta (β)	13 – 30 Hz	Formerly SMR, relaxed yet focused, integrated, Thinking, aware of self & surroundings, Alertness, agitation
Gamma (γ)	30 – 100+ Hz	Motor Functions, higher mental activity

TABLE 1: Wave Types Found in EEG Signals (*adapted from Neurosky Inc. 2009 Brain Wave Signal (EEG) of NeuroSky, Inc.*)

Since an EEG is used to analyzed brain function it is used in clinical practice to:

(i) Diagnose epilepsy and see what type of seizures is occurring. EEG is the most useful and important test in confirming a diagnosis of epilepsy.
(ii) Check for problems with loss of consciousness or dementia.
(iii) Help find out a person's chance of recovery after a change in consciousness.
(iv) Find out if a person who is in a coma is brain-dead.
(v) Study sleep disorders, such as narcolepsy.
(vi) Watch brain activity while a person is receiving general anesthesia during brain surgery.
(vii) Help find out if a person has a physical problem (problems in the brain, spinal cord, or nervous system) or a mental health problem.

Being a physical system however, EEG is subjected to random disturbance. The measurements or observations are generally contaminated with other non-cerebral signals called artifacts or noise caused by the electronic and mechanical components of the measuring devices. These may include EOG (Eye-induced) artifacts (includes eye blinks and eye movements); EKG (Fig 1) (cardiac) artifacts; EMG (muscle activation)-induced artifacts; and Glossokinetic (chewing & sucking movement) artifacts. Artifacts sometimes mimic EEG signals and overlay these signals resulting in distortion making analysis impossible. In clinical practice areas in the reading with artifacts are cancelled resulting in considerable information loss, thus sometimes resulting in misdiagnosis.

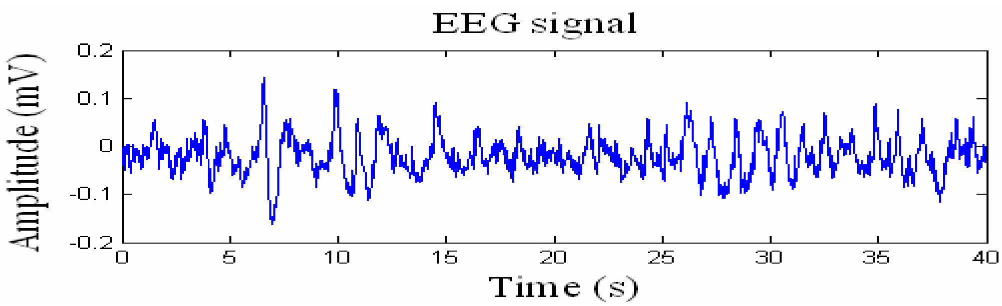

FIGURE 1: EEG Signal corrupted with ECG/EKG and line signals (*adapted from Artifact Removal from EEG Signals using Adaptive Filters In Cascade, A Garcés Correa et al, Journal of Physics: Conference Series 90, 2007)*

Artifacts must be eliminated or attenuated to ensure correct analysis and diagnosis. Through the years there have been different methods of denoising such as artifacts rejection, regression and Principal Components Analysis (PCA). More recently two other methods have been discussed – Independent Component Analysis (ICA) and Wavelet Transform (WT).

2.2 Independent Component Analysis

When a signal is contaminated it is a combination of the true signal S(t) and the artifacts ε(t) producing equation (1) where c(t) is the contaminated signal.

$$c(t) = S(t) + \varepsilon(t) \tag{1}$$

Researchers have been utilizing ICA to remove ε(t).

ICA is an extension of PCA which originated from the field of Blind Source Separation. It is suitable for performing source separation where

(i) sources are independent

(ii) propagation delays of mixing medium are negligible

(iii) source are analog with pdfs not too unlike the gradient of a logistic sigmoid

(iv) the number of independent signals sources is the same as the number of sensors.

Investigations show that EEG satisfies (i) since there are statistically independent brain processes, (ii) since the volume conduction in the brain tissue is efficiently instantaneous. The assumption of (iii) is plausible but the assumption that EEG signals are a linear mixture of exactly N sources is questionable since we are do not know the effective number of statistically independent brain signals contributing to the EEG recorded from the scalp [19]. ICA can therefore be used to performance separations on these signals. There are problems with using ICA however

(i) Its performance depends however on the length of the dataset, because the larger the set the more likely person will have to deal with an over complete ICA which cannot separate artifacts from the signals.

(ii) When ICA performs separations sometimes some useful signals maybe removed as a part of the artifacts resulting in information loss [11].

2.3 Wavelet Transform

Wavelet analysis, a sub brand of applied mathematics has been used to decompose signals in the time frequency scale plane (fig 2). It has been found to be an efficient technique for non-stationary signal processing of which EEG falls. [1] [22]. Its capability to transform the EEG time domain signal into time and frequency localization helps researchers understand more the behaviour of the signals.

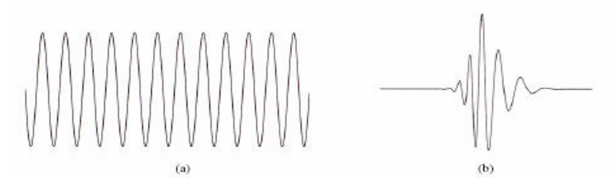

FIGURE 2: Demonstration of (a) a wave and (b) a wavelet. Notice that the wave has an easily discernible frequency while the wavelet has a *pseudo frequency* in that the frequency varies slightly over the length of the wavelet. (*adapted from D.L. Fugal. 2009. Conceptual Wavelets in Digital Signal Processing: An in depth Practical Approach for the Non-Mathematician, Space & Signals Technologies LLC*)

There are two basic types of wavelet transform. One type of wavelet transform is designed to be easily reversible (invertible); that means the original signal can be easily recovered after it has been transformed. This kind of wavelet transform is used for image compression and cleaning (noise and blur reduction). Typically, the wavelet transform of the image is first computed, the wavelet representation is then modified appropriately, and then the wavelet transform is reversed (inverted) to obtain a new image.

The second type of wavelet transform is designed for signal analysis for study of EEG or other biomedical signals. In these cases, a modified form of the original signal is not needed and the wavelet transform need not be inverted (it can be done in principle, but requires a lot of computation time in comparison with the first type of wavelet transform). Decomposition- into wavelets is done by a “mother and “father” wavelet function. These “mother” functions include Haar, Daubechies and Mexican Hat. Equation (2) shows that it is possible to build a wavelet for any function by dilating the mother wavelet function ψ(t) with a coefficient 2^j, and translating the resulting function on a grid whose interval is proportional to 2^{-j}.

$$\Psi_{(a,b)}(t) = 2^{\frac{a}{2}} \psi(2^a t - b) \tag{2}$$

Compressed versions of the wavelet function match the high-frequency components, while stretched versions match the low-frequency components. By correlating the original signal with wavelet functions of different sizes, the details of the signal can be obtained at several scales or moments. These correlations with the different wavelet functions can be arranged in a hierarchical scheme called multi-resolution decomposition. The multi-resolution decomposition algorithm separates the signal into “details” at different moments and wavelet coefficients [22] [23]. These coefficients are called the Discrete Wavelet Transform (DWT) of the signal. As the moments increase the amplitude of the discrete details become smaller however the coefficients of the useful signals increase [27] [28].

If the details are small enough they might be omitted without substantially affecting the main signals. This omission is done through Thresholding. There are two main ways to denoise a signal in WT – soft and hard thresholding. Research as shown that soft-thresholding has better mathematical characteristics [27] [28] and provides smoother results [9]

2.4 Unscented Kalman Filter

Unscented Kalman Filter (UKF) is a Bayesian filter which uses minimum mean-squared error (MMSE) as the criterion to measure optimality [4][34]. For highly nonlinear systems, the linear estimate of the nonlinear model does not provide a good approximation of the model, and the Extended Kalman Filter (EKF) will not track signals around sharp turning points. Another problem with the EKF is that the estimated covariance matrix tends to underestimate the true covariance matrix and therefore risks becoming inconsistent in the statistical sense without the addition of "stabilising noise". UKF was found to address these flaws. It involves the Unscented Transformation (UT), a method used to calculate the first and second order statistics of the outputs of nonlinear systems with Gaussian. The nonlinear stochastic system used for the algorithm is:

$$\begin{aligned} x_{k+1} &= A x_k + B u_k + v_k \\ y_k &= H x_k + w_k \end{aligned} \tag{3}$$

where A and H are the known and constant matrices respectively, x_k is the unobserved state of the system, u_k is a known exogenous input, y_k is the observed measurement signal, v_k is the process noise and w_k is the measurement noise.

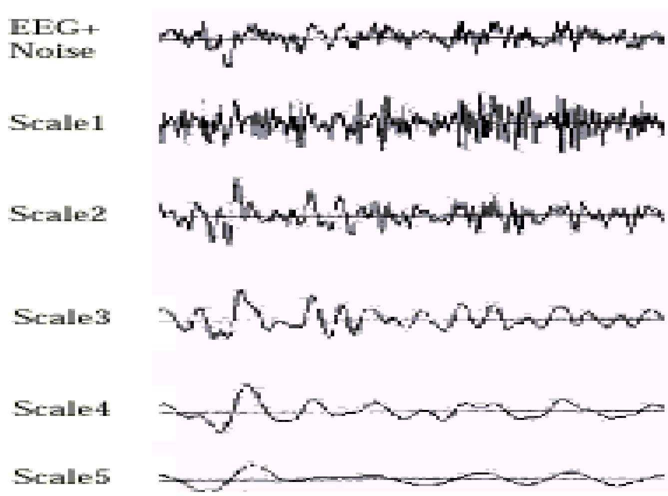

FIGURE 3: Noisy EEG and its Wavelet Transform at different scales (*adapted from Weidong Z., Yingyuan, L. 2001. EEG Multi-resolution Analysis using Wavelet Transform, 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE/EMBS) 2001)*

UKF uses the intuition that it is easier to approximate a probability distribution function rather than to approximate an arbitrary nonlinear function or transformation. Following this intuition, a set of sample points, called sigma points, are generated around the mean, which are thenpropagated through the nonlinear map to get a more accurate estimation of the mean and covariance of the mapping results. In this way, it avoids the need to calculate the Jacobian, which for complex functions can be a difficult task in itself (i.e., requiring complicated derivatives if done analytically or being computationally costly if done numerically).

3. PREVIOUS RESEARCH

WT and ICA in recent years have often been used in Signal Processing. [22] [27]. Although ICA is popular and for the most part does not result in much data loss; its performance depends on the size of the data set i.e. the number of signals. The larger the set, the higher the probability that the effective number of sources will overcome the number of channels (fixed over time), resulting in an over complete ICA. This algorithm might not be able to separate noise from the signals. Another problem with ICA algorithms has to do with the signals in frequency domain. Although noise has different distinguishing features, once they overlap the EEG signals ICA cannot filter them without discarding the true signals as well. This results in data loss.

WT utilizes the distinguishing features of the noise however. Once wavelet coefficients are created, noise can be identified. Decomposition is done at different levels (L); DWT produces different scale effects (Fig 3). Weidong et al. [25] proved that as scales increase the WT of EEG and noise present different inclination. Noise concentrates on scale 21, decreasing significantly when the scale increases, while EEG concentrates on the 22-25 scales. Elimination of the smaller scales denoise the EEG signals. WT therefore removes any overlapping of noise and EEG signals that ICA cannot filter out.

More recently there has been research comparing the denoising techniques of both. It was found
(i) If artifacts and signals are nearly the same or higher amplitude, wavelets had difficultly distinguishing them. ICA on the other hand looks at the underlying distributions thus distinguishing each [29].
(ii) ICA gives high performance when datasets are large. It suffers from the trade off between a small data set and high performance [11].

Research therefore shows that ICA and wavelets complement each other, removing the limitations of each [29]. Since then research as been done applying a combination of both with ICA as a per- or post- denoising tool. Inuso *et al.* [11] used them where ICA and wavelets are joint. They found that their method outperformed the pre- and post- ICA models.

4. RESEARCH DATASETS

EEG data was taken from two sites

(i) http://sccn.ucsd.edu/~arno/fam2data/publicly_available_EEG_data.html. The signals from here are contaminated with EOG. Data is sampled at a rate of 128 samples per second recorded from 32 electrodes at 1000Hz

(ii) http://www.filewatcher.com/b/ftp/ftp.ieee.org/uploads/press/rangayyan.0.0.html. Data was collected at a sampling rate of 1000Hz but noise free. These signals had to artificially contaminated

These two sites produce signals of different sizes as well as 1D and 2D signals.

5. METHODOLOGY

When a signal is decomposed it is represented as a set of wavelet coefficients that correlates to high frequency sub-bands. Artifacts are usually of low frequency and can be removed by shrinkage or thresholding. Research has shown however that thresholding has a slow response [22] [23]. In this paper we are presently another method to denoising using WT and ICA. Some of the ideas appear in earlier algorithms however the main difference of CTICA is the use of cycle spinning; the merger of Wavelet Transform and ICA into one and the improvement of denoising.

The presented method is based on decomposition by using Symmlets which is a near symmetric extension of Daubechies. Symlets are orthogonal and its regularity increases with the increase in the number of moments [6]. After experiments the number of vanishing moments chosen is 8 (Sym8).

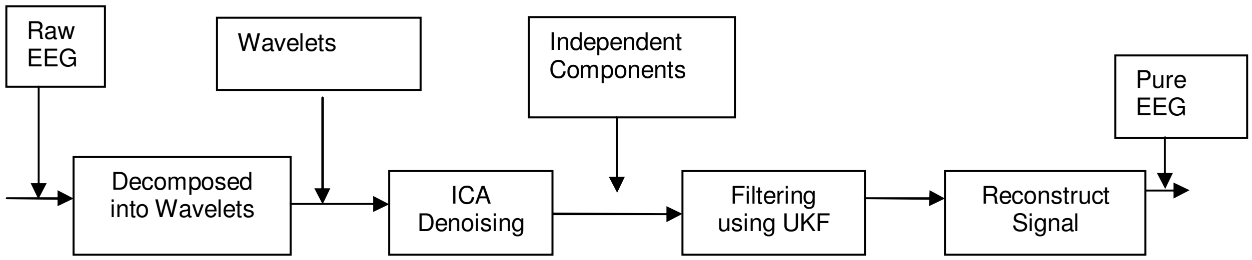

FIGURE 4: Proposed Artifacts Removal System

A block diagram representation of the proposed work is shown in FIGURE 4. EEGs are acquired and Cycle Spinning applied. Cycle Spinning utilizes the periodic time invariance of the wavelet transform to separate noise from signals. The EEG signals are then decomposed by Forward DWT using the Symmlet family of wavelets. The wavelet coefficients are separated into statistically independent sources using ICA and denoising takes place. Each IC is then filtered using UKF. Finally, the sources that are identified as non-artifacts are used to reconstruct the artifact-free EEGs and Cycle Spinning applied again.

6. RESULTS & DISCUSSION

We conducted experiments, using the above mentioned signals, in Matlab 7.8.0 (R2009) on a laptop with AMD Athlon 64x2 Dual-core Processor 1.80GHz. Noisy signals were generated by adding noise to the original noise-free signals and the length of all signals, *N*, were truncated to lengths of power of twos i.e. 2^x.

FastICA	Jade	Radical	CT-ICA
4.1954	4.1909	4.1865	4.1912
7.1276	7.1191	7.1106	7.1192
5.1226	5.1281	5.1226	5.1278
8.0569	8.0484	8.0399	8.0487
7.8736	7.8827	7.8736	7.8815
3.5646	3.5696	3.5646	3.5703
6.0995	6.1057	6.0995	6.1042
2.733	2.7364	2.733	2.7361
0.1374	0.1373	0.1372	0.1373
8.658	8.6521	8.6462	8.6499
0.284	0.2841	0.284	0.2841
0.2234	0.2235	0.2234	0.2235
3.2436	3.2395	3.2355	3.2387

TABLE 2: MSE for 13 EEG signals (x.xe+07)

6.1 Testing Against Known ICA Algorithms

We compared the performance of our method with several state-of-the art ICA algorithms - FastICA, Radical, and Jade. All the algorithms were downloaded from the web sites of the respective authors. In the case of FastICA a symmetrical view based on the tan score function was used for comparison. To determine the quality of each signal the Mean Square Error (MSE), the Peak Signal to Noise Ratio (PSNR), the Signal to Distortion Ratio (SDR), the Signal to noise Ratio (SNR) and the Amari Performance Index were calculated.

MSE measures the average of the square of the "error" and defined as:

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y) - I'(x,y)]^2 \tag{4}$$

The error is the amount by which the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate. TABLE 2 shows the MSE for 13 signals. Observations show that there is not much difference in the MSE for each algorithm. The lower the MSE the lesser the error on the signal; it can seen that on average our method performed better than FastICA and Jade. Radical had a lower MSE.

FastICA	Jade	Radical	CT-ICA
-18.0969	-18.0923	-18.0877	-18.0926
-20.3987	-20.3935	-20.3883	-20.3935
-18.9641	-18.9687	-18.9641	-18.9685
-20.9309	-20.9263	-20.9217	-20.9265
-20.8309	-20.836	-20.8309	-20.8353
-17.3893	-17.3954	-17.3893	-17.3962
-19.7221	-19.7266	-19.7221	-19.7255
-16.2355	-16.241	-16.2355	-16.2405
-23.2477	-23.2453	-23.243	-23.2442
-21.2434	-21.2404	-21.2375	-21.2393
-26.4025	-26.4042	-26.4025	-26.404
-25.359	-25.3609	-25.359	-25.3611
-16.9794	-16.974	-16.9686	-16.9729

TABLE 3: PSNR for 13 EEG signals

PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. It is defined as:

$$PSNR = 10 \times \log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{5}$$

Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. In this research MAX takes the value of 255. Tab 3 shows the PSNR for 13 signals. If the PSNR is high then the ratio of signal to noise is higher and therefore the algorithm is considered good.

After experiments it can be seen that our algorithm has the same PSNR on average. It was also seen that it has a higher PSNR than Jade and Radical. The similar signal to noise ratio can be seen in the SNR graph in figure 5 where only Jade has a different value.

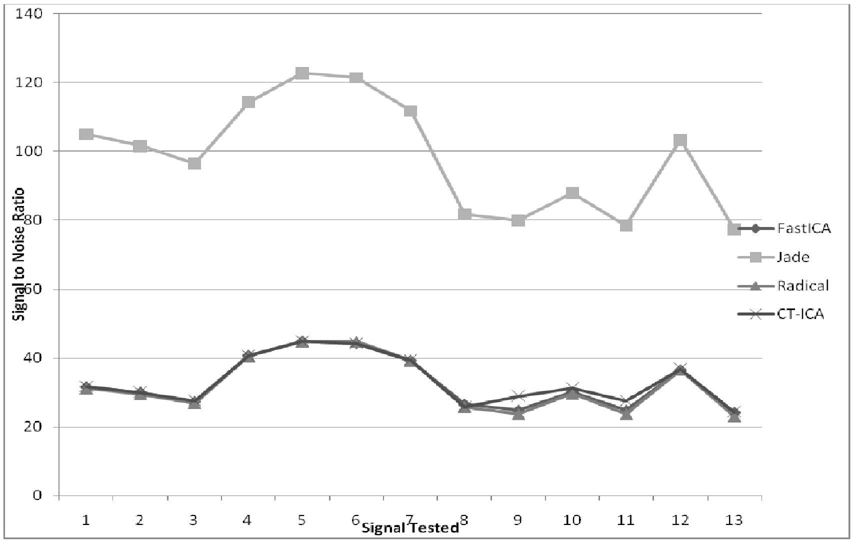

FIGURE 5: SNR results for 13 signals

The accuracy of the separation for each algorithm in terms of the signals can be calculated by the total SDR defined as:

$$SDR(x_i, y_i) = \frac{\sum_{n=1}^{L} x_i(n)^2}{\sum_{n=1}^{L} \left(y_i(n) - x_i(n) \right)^2} \quad i = 1, \ldots m \tag{6}$$

where $x_i(n)$ is the original source signal and $y_i(n)$ is the reconstructed signal. When SDR are calculated any found below 8-10dB are considered to fail separation. Fig 5 shows that all four algorithms had SDR above 8dB. It also shows that CTICA had SDR very close to the other four so that there was no differentiation in the graph.

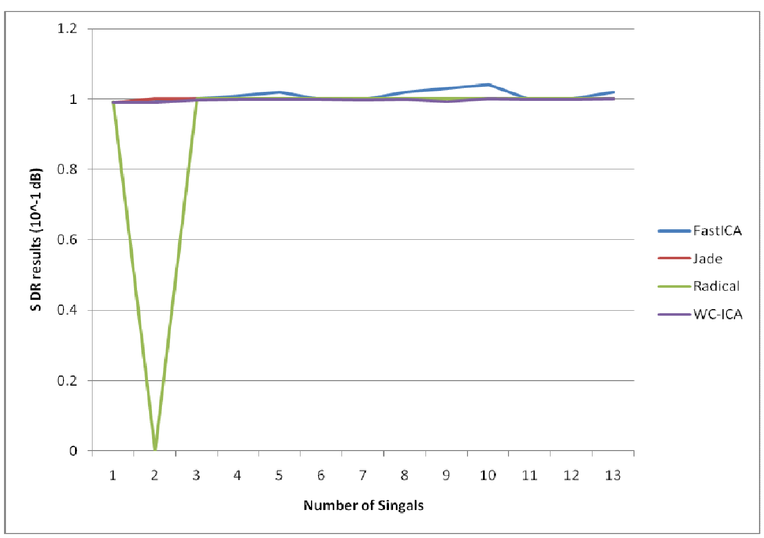

FIGURE 6: SDR results for 13 signals

The global accuracy of the separation of each algorithm was tested using the Amari performance index defined as:

$$P_{err} = \frac{1}{2m}\sum_{i,j=1}^{m}\left(\frac{|p_{ij}|}{\max_k |p_{ik}|}+\frac{|p_{ij}|}{\max_k |p_{kj}|}\right)-1 \tag{7}$$

where $p_{ij} = (BA)_{ij}$. It assesses the quality of the de-mixing matrix **W** for separating observations generated by the mixing matrix **A.** The lower the Amari index, the more accurate the separation is. We have normalized all values of the Amari index to be between 0 and 1 (the max). The Amari indexes obtained for the different algorithms and for different sample sizes are presented in TABLE 4. Observations show that the Amari indexes for our method is very similar to those of Jade and FastICA. On average however it has a lower Amari than both FastICA and Jade but not Radical.

FastICA	Jade	Radical	CT-ICA
1238	1237	1236	1237
1583	1582	1581	1582
1363	1363	1363	1363
1669	1668	1667	1668
1652	1653	1652	1653
1140	1141	1140	1141
1477	1478	1477	1478
989	990	989	990
2069	2068	2068	2068
1720	1720	1719	1720
2683	2683	2683	2683
2471	2471	2471	2471
1085	1085	1084	1084

TABLE 4: Amari Test Results for 13 EEG signals (x.xe-05)

6.2 Testing against Known WT-influenced Algorithms

Zhou et al. [28] in 2004 found that a combination of wavelet threshold de-noising and ICA resulted in the removal of electromyogram (EMG) and electrocardiograph (ECG) artifacts from EEG signals. Further research in 2007 by Inuso et al. [11] resulted in the creation of a new technique for EEG artifact removal, based on the joint use of Wavelet transform and Independent Component Analysis (WICA). After comparison to pre- and post- ICA and wavelet denoising using artificial artifact-laden EEG datasets they found that this combination had the best artifact separation performance for every kind of artifact also allowing for the minimum information loss. These show that a merger of WT and ICA is more effective.

Pre-WT	Post-WT	WT-UKF	WT-ICA	CT-ICA
33.9443	1.1158e3	1.1025	1.1051	1.0947
29.0936	1.0438	1.0499	1.0379	1.0372
23.9498	1.0058	997.4019	982.4991	979.2423

TABLE 5: Sample MSE for 3 EEG signals

Sameni et al. [21] experimented with denoising using EKF on ECG data. They found that the results show that the EKF may be used as a powerful tool for the extraction of the ECG signals from noisy measurements. Jacob and Martin [12] tested a combination of WT and Weiner Filter. They concluded that this combination basic denoising using only WT

Pre-WT	Post-WT	WT-UKF	WT-ICA	CT-ICA
32.8231	17.655	17.7071	17.6966	17.7377
33.4928	17.9446	17.9192	17.9693	17.9722
34.3378	18.1058	18.1421	18.2075	18.2219

TABLE 6: Sample PSNR for 3 EEG signals

As stated before ICA and WT complement each other, removing the limitations of each [29]; researchers have shown that the combination of WT and ICA is more effective than ICA or WT alone supporting this theory. They have also shown that the performance of WT improves with the addition of Filters. In our research investigations have shown that when compared to the post- and pre- ICA models, a combination of WT with (i) ICA, or (ii) UKF we have found as seen in Tables 5 and 6 that the merger of all three outperformed all except the Pre-ICA model. This conforms to the findings of researchers.

7. CONCLUSION

In recent years researchers have used both ICA algorithms and WT to denoise EEG signals. In this paper we propose a new method – Cycle Spinning Wavelet Transform ICA (CTICA). From the experiments we can conclude the following for CTICA

(I) It can be seen from the experiments that it can successfully separate noise from EEG signals.
(II) It has outperformed FastICA and JADE as far as MSE was concerned,
(III) It has outperformed JADE and Radical with PSNR.
(IV) It has the similar in SDR and Amari index
(V) It outperforms different WT model designs except for the Pre-ICA model.

Based on these results it can be concluded that CTICA has an overall performance which is better than all three ICA algorithms and most WT model, i.e. it is the most consistent and robust denoising method.

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