

# Improving the Performance of Translation Wavelet Transform using BMICA

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**Abstract**—Research has shown Wavelet Transform to be one of the best methods for denoising biosignals. Translation-Invariant form of this method has been found to be the best performance. In this paper however we utilize this method and merger with our newly created Independent Component Analysis method – BMICA. Different EEG signals are used to verify the method within the MATLAB environment. Results are then compared with those of the actual Translation-Invariant algorithm and evaluated using the performance measures Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Signal to Distortion Ratio (SDR), and Signal to Interference Ratio (SIR). Experiments revealed that the BMICA Translation-Invariant Wavelet Transform out performed in all four measures. This indicates that it performed superior to the basic Translation-Invariant Wavelet Transform algorithm producing cleaner EEG signals which can influence diagnosis as well as clinical studies of the brain.

**Keywords**-B-Spline; Independent Component Analysis; Mutual Information; Translation-Invariant Wavelet Transform

## I. INTRODUCTION

The nervous system sends commands and communicates by trains of electric impulses. When the neurons of the human brain process information they do so by changing the flow of electrical current across their membranes. These changing currents (potentials) generate electric fields that can be recorded from the scalp. Studies are interested in these electrical potentials but they can only be received by direct measurement. This requires a patient to under-go surgery for electrodes to be placed inside the head. This is not acceptable because of the risk to the patient [25]. Researchers therefore collect recordings from the scalp receiving the global descriptions of the brain activity. Because the same potential is recorded from more than one electrode, signals from the electrodes are supposed to be highly correlated. Figure 1 shows how the potentials are collected from the scalp. These are collected by the use of an electroencephalograph and called electroencephalogram (EEG) signals.

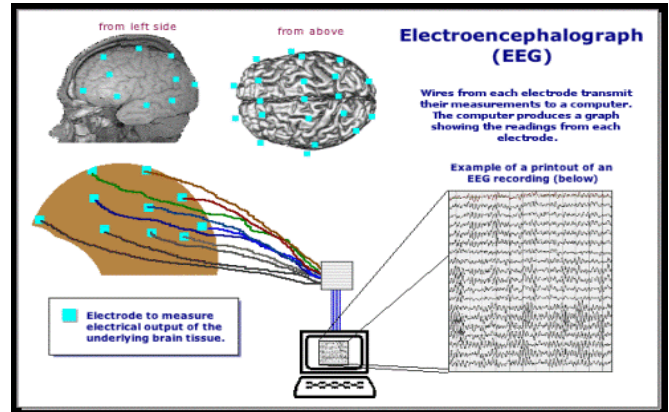


Figure 1: Collecting EEG signals

EEG is widely used by physicians and scientists to study brain function and to diagnose neurological disorders. Any misinterpretations can lead to misdiagnosis. These signals must therefore present a true and clear picture about brain activities as seen in Figure 2. EEG signals are however highly attenuated and mixed with non-cerebral impulses called **artifacts** or **noise** [15]. The presence of these noises introduces spikes which can be confused with neurological rhythms. They also mimic EEG signals, overlaying these signals resulting in signal distortion (Figure3). Correct analysis is therefore impossible; a true diagnosis can only be seen when all these noises are eliminated or attenuated. EEG recordings are really therefore a combination of noise and the pure EEG signal defined mathematically below (using  $S$  as the pure EEG signal,  $N$  the noise and  $E$  representing the recorded signal):

$$E(t) = S(t) + N(t) \quad (1)$$

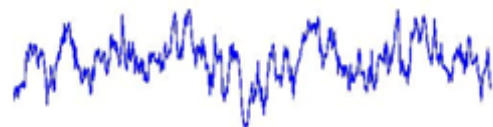


Figure 2: Clean pure EEG Signal

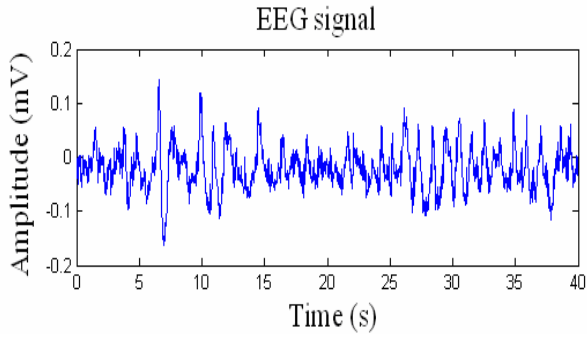


Figure 3: EEG Signal corrupted with EKG and line signals

Numerous methods have been proposed by researchers to remove artifacts in EEG and are reviewed in [6, 13, 20, 22, 24]. The goal of these methods is to decompose the EEG signals into spatial and temporal distinguishable components. After identification of components constituting noise, the EEG is reconstructed without them. Methods include Principal Components Analysis (PCA), the use of a dipole model and more recently Independent Component Analysis (ICA) and Wavelet Transform (WT). Which method is considered the best is not the topic of this research. Here we focus on improving WT using a new ICA method called – B-Spline Mutual Information Independent Component Analysis (BMICA).

The paper is organized as follows: after this introduction of EEG signals and the need to denoise Section 2 presents the denoising methods utilized in the paper. We then review the reasons for merger in Section 3 and describe the experiments conducted in Section 4. In Section 5 we present the results, comparison of these results and a summary. Finally in Section 6 we present the conclusion.

## II. LITERATURE REVIEW

### A. Wavelet Transform

Wavelet Transform (WT) is a form of time-frequency analysis been used successfully in denoising biomedical signals by decomposing signals in the time-scale space instead of time-frequency space. It is so because it uses a method called wavelet shrinkage proposed by Donoho and Johnstone [7]. Each decomposed signal is called a wavelet. Figure 4 shows the difference between a wave/signal and a wavelet.

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

appropriately, and then the WT is reversed (inverted) to obtain a new image.

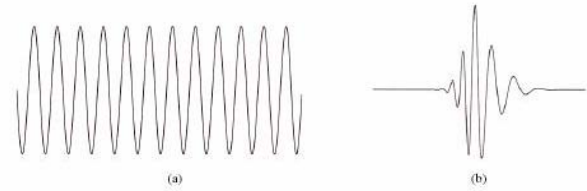


Figure 4. Demonstration of (a) a signal and (b) a wavelet

The second type 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 WT need not be inverted (it can be done in principle, but requires a lot of computation time in comparison with the first type of WT).

WT decomposes a signal into a set of coefficients called the discrete wavelet transform (DWT) according to:

$$C_{j,k} = \sum_{t \in \mathbb{Z}} E(t) g_{j,k}(t) \quad (2)$$

where  $C_{j,k}$  is the wavelet coefficient and  $g_{j,k}$  is the scaling function defined in [23] as:

$$2^{-\frac{j}{2}} g(2^{-j}t - k) \quad (3)$$

The wavelet and scaling functions depend on the chosen wavelet family, such as Haar, Daubechies and Coiflet. 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 [19-20]. As the moments increase the amplitude of the discrete details become smaller, however the coefficients of the useful signals increase [27-28].

Considering Eq. (1) the wavelet transform of  $E(t)$  produces wavelet coefficients of the noiseless signal  $S(t)$  and the coefficients of the noise  $N(t)$ . Researchers found that wavelet denoising is performed by taking the wavelet transform of the noise-corrupted  $E(t)$  and passing the detail coefficients, of the wavelet transform, through a threshold filter where the details, if small enough, might be omitted without substantially affecting the main signals. There are two main threshold filters – soft and hard. Research as shown that soft-thresholding has better mathematical characteristics [27-29] and provides smoother results [10]. Once discarded these coefficients are replaced with zeroes during reconstruction using an inverse

wavelet transform to yield an estimate for the true signal, defined as:

$$\hat{S}(t) = D(E(t)) = W^{-1}(\Lambda_{th}(W(E(t)))) \quad (4)$$

where  $\Lambda_{th}$  is the diagonal thresholding operator that zeroes out wavelet coefficients less than the threshold,  $th$ . It has been shown that this algorithm offers the advantages of smoothness and adaptation. It has been shown that this algorithm offers the advantages of smoothness and adaptation however it may also result in a blur of the signal energy over several transform details of smaller amplitude which may be masked in the noise. This results in the detail been subsequently truncated when it falls below the threshold. These truncations can result in overshooting and undershooting around discontinuities similar to the Gibbs phenomena in the reconstructed denoised signal. Coifman and Donoho [4] proposed a solution by designing a cycle spinning denoising algorithm which

- (i) shifts the signal by collection of shifts, within range of cycle spinning
- (ii) denoise each shifted signal using a threshold (hard or soft)
- (iii) inverse-shift the denoised signal to get a signal in the same phase as the noisy signal
- (iv) Averaging the estimates.

The Gibbs artifacts of different shifts partially cancel each other, and the final estimate exhibits significantly weaker artifacts [4]. This method is called a translation-invariant (TI) denoising scheme. Experimental results in [1] confirm that single TI wavelet denoising performs better than the traditional single wavelet denoising. Research has also shown that TI produces smaller approximation error when approximating a smooth function as well as mitigating Gibbs artifacts when approximating a discontinuous function.

### B. Independent Component Analysis

*Independent Component Analysis* (ICA) is an approach for the solution of the BSS problem [5]. It can be represented mathematically according to Hyvarinen, Karhunen & Oja [12] as:

$$X = As + n \quad (5)$$

where  $X$  is the observed signal,  $n$  is the noise,  $A$  is the mixing matrix and  $s$  the independent components (ICs) or sources. (It can be seen that mathematically it is similar to Eq. 1). The problem is to determine  $A$  and recover  $s$  knowing only the measured signal  $X$  (equivalent to  $E(t)$  in Eq. (1)). This leads to finding the linear transformation  $W$  of  $X$ , i.e. the inverse of the mixing matrix  $A$ , to determine the independent outputs as:

$$u = WX = WAs \quad (6)$$

where  $u$  is the estimated ICs. For this solution to work the assumption is made that the components are statistically independent, while the mixture is not. This is plausible since biological areas are spatially distinct and generate a specific activation; they however correlate in their flow of information [11].

ICA algorithms are suitable for denoising EEG signals because

- (i) the signals recorded are the combination of temporal ICs arising from spatially fixed sources
- (ii) the signals tend to be transient (localized in time), restricted to certain ranges of temporal and spatial frequencies (localized in scale) and prominent over certain scalp regions (localized in space) [20].

### B-Spline Mutual Information Independent Component Analysis (BMICA)

There have been many Mutual Information (MI) estimators in ICA literature which are very powerful yet difficult to estimate resulting in unreliable, noisy and even bias estimation. Most algorithms have their estimators based on cumulant expansions because of ease of use [16]. B-Spline estimators according to our previous research [26] however, have been shown to be one of the best nonparametric approaches, second to only wavelet density estimators. In numerical estimation of MI from continuous microarray data, a generalized indicator function based on B-Spline has been proposed to get more accurate estimation of probabilities; hence we have designed a B-Spline defined MI contrast function. Our MI function is expressed in terms of entropy as:

$$I(X, Y) = H(X) + H(Y) - H(X, Y) \quad (7)$$

where

$$\begin{aligned} H(X) &= -\sum_i p(x_i) \log p(x_i) \\ H(X, Y) &= -\sum_{i,j} p(x_i, y_j) \log p(x_i, y_j) \end{aligned} \quad (8)$$

Eq. (6) contains the term  $-H(X, Y)$ , which means that maximizing MI is related to minimizing joint entropy. MI is better than joint entropy however because it includes the marginal entropies  $H(X)$  and  $H(Y)$  [13]. Entropy in our design is based on probability distribution functions (pdfs) and our design defines a pdf using a B-Spline calculation resulting in

$$p(x_i) = \frac{1}{N} \sum_{u=1}^N \tilde{B}_{i,k}(x_u) \quad (9)$$

where

$$B(x) = \sum_{i=1}^{n+1} D_i B_{i-k}^k(x) \quad (10)$$

and  $D_I$  is calculated based on Cheney and Kincaid (1994).

MI was used to create our fixed-point Independent Component Analysis algorithm called B-Spline Mutual Information Independent Component Analysis (BMICA). BMICA utilizes prewhitening strategies as well as possess the linearity  $g(u) = \tanh$  and a symmetric orthogonalization. Unmixed signals are determined by:

$$B = (zg(y)' / m - \sum (1 - g(y)^2)' \times I) / m \quad (11)$$

where  $z$  is the result of prewhitening and  $y$  is the whitened signal determined by

$$y = z' \times B \quad (12)$$

### III. REASONS FOR MERGER

WT and ICA in recent years have often been used in Signal Processing [21, 27]. More recently there has been research comparing the denoising techniques of both. It was found

- (i) if noise and signals are nearly the same or higher amplitude, wavelets had difficulty 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 [13]. The larger the set, however 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.
- (iii) ICA algorithms cannot filter noise that is overlapping with EEG signals without discarding the true signals as well. This results in data loss. With WT however once wavelet coefficients are created, noise can be identified as they concentrate on scale  $2^l$  decreasing significantly when the scale increases, while EEG concentrates on the  $2^2$ - $2^5$  scales. Elimination of the smaller scales denoise the EEG signals [1]. WT therefore removes any overlapping of noise and EEG signals that ICA cannot filter out.

Research therefore shows that ICA and wavelets complement each other, removing the limitations of each [21].

### IV. EXPERIMENT SETUP

#### A. Data Sets

There are two types of data that can be used in experiments – real and synthetic. In synthetic data the source signals are known as well as the mixing matrix  $A$ . In these cases the separation performance of the unmixing matrix  $W$  can be assessed using the known  $A$  and the quality of the unmixed

signals  $y_i$  can be evaluated using the known source  $s_i$ . Biomedical signals however produce unknown source signals. In this study therefore we utilize real data collected from four sites.

- (i) [http://sccn.ucsd.edu/~arno/fam2data/publicly\\_available\\_EEG\\_data.html](http://sccn.ucsd.edu/~arno/fam2data/publicly_available_EEG_data.html). All data are real comprised of EEG signals from both human and animals. Data were of different types.
  - (a) Data set acquired is a collection of 32-channel data from one male subject who performed a visual task.
  - (b) Human data based on five disabled and four healthy subjects. The disabled subjects (1-5) were all wheelchair-bound but had varying communication and limb muscle control abilities. The four healthy subjects (6-9) were all male PhD students, age 30 who had no known neurological deficits. Signals were recorded at 2048 Hz sampling rate from 32 electrodes placed at the standard positions of the 10-20 international system.
  - (c) Data set is a collection of 32-channel data from 14 subjects (7 males, 7 females) who performed a go-nogo categorization task and a go-no recognition task on natural photographs presented very briefly (20 ms). Each subject responded to a total of 2500 trials. The data is CZ referenced and is sampled at 1000 Hz.
  - (d) Five data sets containing quasi-stationary, noise-free EEG signals both in normal and epileptic subjects. Each data set contains 100 single channel EEG segments of 23.6 sec duration.
- (ii) <http://www.cs.tut.fi/~gomezher/projects/eeg/database.s.htm>. Data here contains
  - (a) Two EEG recordings (linked-mastoids reference) from a healthy 27-year-old male in which the subject was asked to intentionally generate artifacts in the EEG
  - (b) Two 35 years-old males where the data were collected from 21 scalp electrodes placed according to the international 10-20 System with addition electrodes T1 and T2 on the temporal region. The sampling frequency was 250 Hz and an average reference montage was used. The electrocardiogram (ECG) for each patient was also simultaneously acquired and is available in channel 22 of each recording.
- (iii) <http://idiap.ch/scientific-research/resources/>. Data here comes from 3 normal subjects during non-feedback sessions. The subjects sat in a normal chair, relaxed arms resting on their legs
- (iv) [sites.google.com/site/projectbci](http://sites.google.com/site/projectbci). Data here is from a 21 age year old right-handed male with no medical conditions. EEG consists of actual random movement of left and right hand recordings with eyes closed. Each row represents one electrode. The order of electrode is FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2,

F7, F8, T3, T4, T5, T6, F2, CZ, PZ. Recording was done at 500Hz using Neurofax EEG system.

These four sites produce real signals of different sizes however all were 2D signals.

### B. Methodology

In this paper we are comparing the merger of BMICA with TIWT with the results of the normal TIWT. In this research the TIWT method for both tests involves the following steps:

#### 1. Signal Collection

This algorithm is designed to denoise both natural and artificially noised EEG signals. They should therefore be mathematically defined based on Eq. (1).

#### 2. Apply CS to signal

The number of time shifts is determined; in so doing signals are forcibly shifted so that their features change positions removing the undesirable oscillations which result in pseudo-Gibbs phenomena. The circulant shift by  $h$  is defined as:

$$S_h(f(n)) = f((n+h) \bmod N) \quad (13)$$

where  $f(n)$  is the signal,  $S$  is time shift operator and  $N$  is the number of signals. The time-shift operator  $S$  is unitary and therefore invertible i.e.  $(S_h)^{-1} = S_{-h}$

#### 3. Decomposition of Signal

The signals are decomposed into 5 levels of DWT using the Symmlet family, separating noise and true signals. Symmlets are orthogonal and its regularity increases with the increase in the number of moments [8]. After experiments the number of vanishing moments chosen is 8 (Sym8).

#### 4. Choose and Apply Threshold Value

Denoise using the soft-thresholding method discarding all coefficients below the threshold value using HardShrink based on the universal threshold defined by Donoho & Johnstone [7] given as:

$$T = \sqrt{2\sigma^2 \log N} \quad (14)$$

where  $N$  is the number of samples and  $\sigma^2$  is the noise power.

#### 5. Reconstruction of Signals

EEG signals are reconstructed using inverse DWT.

#### 6. Apply CS

Revert signals to their original time shift and average the results obtained to produce the denoised EEG signals.

The proposed algorithm can be expressed as Avg [Shift - Denoise -Unshift] i.e. using Eq. (8) it is defined as:

$$avg_{h \in H} (S_{-h} T S_h (f)) \quad (15)$$

where  $H$  is the range of shifts,  $T$  is the wavelet shrinkage denoising operator,  $h$  the circular shift and the maximum of  $H$  is the length of the signal  $N$  from Eq. (8).

### C. Performance Matrix

The analysis of the algorithm performance consisted in estimating (1) the accuracy with which each algorithm was able to separate components, and (2) the speed with which each algorithm was able to reproduce EEG signals. For (1) experiments were mainly aimed at assessing the algorithms' ability to perform ICA (extraction of ICs) and not blind source separation (recovery of original sources). The performance measures that will be used throughout are based on two categories of calculation:

1. Separation Accuracy Measures - Signal to Distortion Ratio (SDR), Signal to Interference Ratio (SIR), and
2. Noise/Signal Measures - Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR).

Testing on (2) was not executed.

## V. RESULTS/DISCUSSION

Experiments were conducted using the above mentioned signals, in Matrix Laboratory (MATLAB) 7.10.0.499 (R2010) on a laptop with AMD Athlon 64x2 Dual-core Processor 1.80GHZ. Figure 5 shows one mixed EEG signal set where there are overlays in signals Nos. 6-8 and Nos. 14-18. Figures 6 and 7 show the same signal set after applying TIWT and BMICA-TIWT merger showing that the overlays have been minimized - noise has been removed. With BMICA-TIWT it can be seen that more noise have been eliminated especially in signals Nos. 14-18.

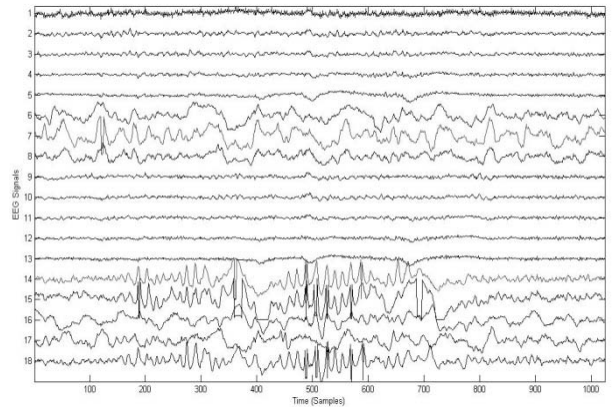


Figure 5: Raw EEG

$$SIR(dB) = \frac{1}{n} \sum_{i=1}^n \left( \sum_j \frac{|p_{ij}|}{\max_k |p_{ij}|} - 1 \right) \quad (16)$$

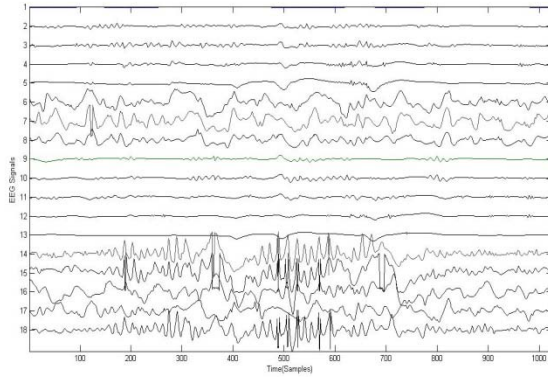


Figure 6: WT

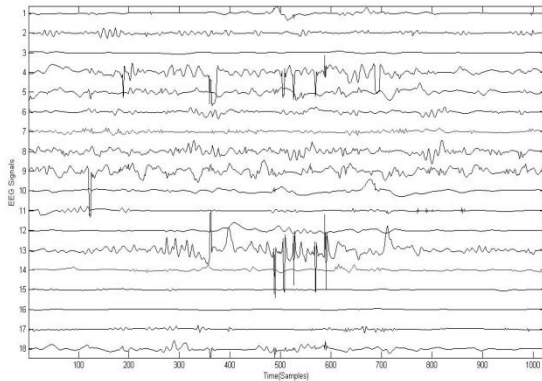


Figure 7: BMICA-WT

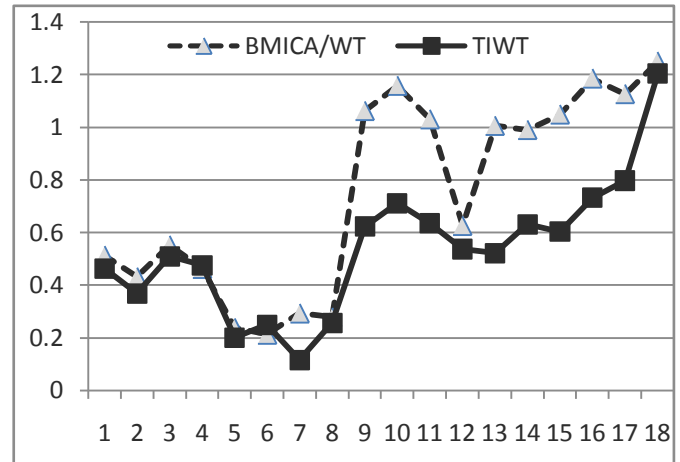


Figure 8: SIR relations between BMICA-WT and TIWT

SIR takes into account the fact that, in general, BSS is able to recover the sources only up to (a permutation and) a gain factor  $\alpha$ . It is easy to check that if  $\hat{s}_i = \alpha s_i$  the SIR is infinite. By contrary, when the estimated source is orthogonal to the true source, the SIR is equal to zero.

Investigations on the EEG data sets described above showed that BMICA-WT produced higher SIR calculations than TIWT. This can be seen in Figure 8 where for 18 signal sets BMICA-WT produced SIR higher 94% of the time. This suggests that when merger with BMICA, TIWT achieved better separation of EEG signals.

### A. Separation Accuracy Measures

#### SIR

The most common situation in many applications is the degenerate BSS problem, i.e.  $n < m$ . This is most likely the case when we try to separate the underlying brain sources from electroencephalographic (EEG) or magnetoencephalographic (MEG) recordings using a reduced set of electrodes. In degenerate demixing, the accuracy of a BSS algorithm cannot be described using only the estimated mixing matrix. In this case it becomes of particular importance to measure how well BSS algorithms estimate the sources with adequate criteria. The most commonly used index to assess the quality of the estimated sources is the Signal to Interference Ratio (SIR) [14]

#### SDR

While SIR assesses the quality of the estimated sources, and the Amari Index assess the accuracy of the estimated mixing matrix, the accuracy of the separation of an ICA algorithm in terms of the signals (i.e. the overall separation performance) is calculated by the total Signal to Distortion Ratio (SDR) defined as:

$$SDR(x_i, y_i) = \frac{\sum_{n=1}^L x_i(n)^2}{\sum_{n=1}^L (y_i(n) - x_i(n))^2} \quad i = 1, \dots, m, \quad (17)$$

where  $x_i(n)$  is the original source signal and  $y_i(n)$  is the reconstructed signal. The SDR is expressed in decibels (dB). The higher the SDR value, the better the separation of the signal from the noise. When the SDR is calculated if it is found to be below 8-10dB the algorithm is considered to have failed separation.

Examinations of experiment results show that BMICA-WT tends to produce higher SDRs. In Table 1 it can be seen that

BMICA-TIWT produces higher SDR 65% of the time. This indicates that almost every TIWT testing there is a BMICA-TIWT test which produces a more accurate separation of signal and noise.

TABLE I: SDR FOR 19 EEG SIGNAL SETS

BMICA-WT	TIWT
3.54E+03	2.14E+03
-88.843	-1.27E+02
-57.376	-80.281
-112.4126	-121.4977
-564.4613	-640.939
-217.66	-260.2769
-2.48E+03	-3.40E+03
-8.62E+04	-8.57E+04
27.0891	-0.002
4.77E+04	1.39E+03
6.80E+02	7.67E+02
2.38E+03	786.5632
2.73E+02	269.5584
1.83E+03	1.66E+03
1.12E+00	7.08E+02
6.50E+02	9.97E+02
8.55E+02	8.81E+02
4.74E+02	9.95E+02
2.71E+04	2.13E+04

B. Noise/Signal Measures

PSNR

Peak Signal-to-Noise Ratio, often abbreviated as PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

$$PSNR = 10 \times \log_{10} \left( \frac{MAX^2}{MSE} \right). \tag{18}$$

Figure 9 shows the relationship between BMICA-TIWT and TIWT for PSNR. Close examinations show that for all 18 signal sets the PSNR for BMICA-TIWT were higher than those of TIWT. BMICA-TIWT therefore produces a better quality of the reconstructed signal i.e. it produces a signal of a higher quality and therefore can be considered a better algorithm for denoising.

In this research MAX takes the value of 255. Unlike MSE which represents the cumulative squared error between the denoised and mixed signal, PSNR represents a measure of the peak error i.e. when the two signals are identical the MSE will be equal to zero, resulting in an infinite PSNR. The higher the PSNR, therefore, the better the quality of the reconstructed signal i.e. a higher PSNR indicates that the reconstruction is of a higher quality and therefore the algorithm is considered good.

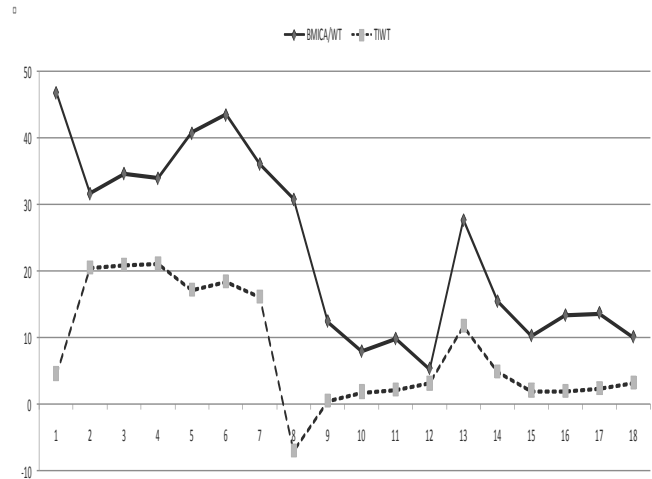


Figure 9: PSNR relations between BMICA-WT and TIWT

MSE

The Mean Square Error (MSE) measures the average of the square of the “error” which is the amount by which the estimator differs from the quantity to be estimated. The difference occurs because of the randomness or because the estimator doesn't account for information that could produce a more accurate estimate. MSE thus assesses the quality of an estimator in terms of its variation and unbiasedness. Note that the MSE is not equivalent to the expected value of the absolute error.

$$MSE = \frac{1}{N} \sum_{y=1}^N [I(x, y) - I'(x, y)]^2. \tag{19}$$

Since MSE is an expectation, it is a scalar, and not a random variable. It may be a function of the unknown parameter  $\theta$ , but it does not depend on any random quantities. However, when MSE is computed for a particular estimator of  $\theta$  the true value of which is not known, it will be subject to an estimation error. In a Bayesian sense, this means that there are cases in which it may be treated as a random variable.

Examination of the experiments shows that BMICA-WT produces smaller MSE than TIWT; see Table 2. Normally MSE is indirectly proportional to PSNR, i.e. when MSE calculated is equal to zero, then PSNR is infinite. A good algorithm will therefore have a small MSE and a large PSNR. Investigations show that BMICA-TIWT produces smaller MSE and larger PSNR than TIWT – better algorithm as it produces results closer to the actual data.

TABLE II. SDR FOR 19 EEG SIGNAL SETS

BMICA-WT	TIWT
1.33E+03	2.27E+04
44.032	583.0681
21.863	529.9447
25.8048	501.1608
5.404	1.24E+03
2.8685	917.3362
15.7071	1.57E+03
53.7782	3.25E+05
3.67E+03	5.94E+11
1.04E+04	4.24E+04
6.74E+03	4.01E+04
1.90E+04	3.16E+04
1.10E+02	4.33E+03
1.84E+04	2.13E+04
6.06E+03	4.05E+04
2.98E+03	4.08E+04
2.75E+03	3.72E+04
6.32E+03	3.15E+04

## VI. CONCLUSIONS

Research have found that WT is the best suited for denoising as far as performance goes because of its properties like sparsity, multiresolution and multiscale nature. Non-orthogonal wavelets such as UDWT and Multiwavelets improve the performance at the expense of a large overhead in their computation [28]. Research also shows that TIWT is considered to be an improvement on WT, removing Gibbs phenomena. In this work we have found that the addition of BMICA to TIWT has been found to improve its performance. With the BMICA merger the separation accuracy of TIWT increased although it was not so 100% of time with SDR. As far as the noise/signal separation goes however the merger produces a better quality reconstructed signal 100% of the time.

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