Electroencephalogram Signal Eye Blink Rejection Improvement Based on the Hybrid Stone Blind Origin Separation and Particle Swarm Optimization Technique

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This work was supported by the International Exchange Program of the South China University of Technology.

ABSTRACT Electroencephalogram (EEG) extraction has widely used Stone’s Blind Source Separation (Stone’s BSS) algorithm. However, Stone’s BSS algorithm is sensitive to the initial half-life ($h_{long}$, $h_{short}$) and weight vector W parameters, which affect the convergence of the algorithm. This paper proposes a hybridization of Stone’s BSS with Particle Swarm Optimization (PSO) to boost the separation process. An improved Stone’s BSS (ISBSS) method is employed to reject eye blinking from the electroencephalogram (EEG) mixture. The electroencephalogram (EEG) mixed-signal is first centralized and whitened; then, it is incorporated into the particle swarm optimization (PSO) iterative algorithm to process the initial ($h_{long}$, $h_{short}$) and generate the weight vector W parameters randomly. Finally, the generalized eigenvalue decomposition (GEVD) method is applied to extract EEG singles to obtain a clean EEG signal. A clinical EEG database is used to test the improved and other algorithms. The GEVD method estimates the measurement performance of the proposed algorithm using a carrier-to-interference ratio and integral square error and compares the proposed algorithm with the conventional Stone’s BSS, fast independent component analysis (FastICA), evolutionary fast independent component analysis (EFICA), and joint approximate diagonalization of eigen matrices (JADE) algorithms to check its effectiveness. The results show that the suggested hybrid method has a better performance and decreasing elapsed time than conventional Stone’s BSS and other algorithms.

INDEX TERMS Electroencephalogram (EEG), eye blinking, particle swarm optimization, signal analysis, stone’s BSS technique.

I. INTRODUCTION

In biomedical signal processing science, electroencephalography is a method used to present the efficiency of the human brain. Electroencephalogram (EEG) signals are generated from the reciprocal activities connected with cortical neurons. Brain efficiency is determined by sensing elements attached to the patient’s head [1]. In 1929, the first paper was published, which depicted the system for identifying the performance of the human brain. The essential characteristics of EEG signals are noted without difficulty by sensing elements (electrodes), compound spatiotemporal reference, ideal for time-based arrangements, and reliance on the magnitude of electrodes [2].

The EEG signals consist of a mixed-signal with unwanted signals during the recording process, such as eye blinking and power equipment noises, which make it difficult to understand the EEG brain activity. The EEG signals, which are in microvolts and a frequency range of 0–64 Hz, are contaminated by eye blinking in the 0–16-Hz frequency range. Such an unwanted mixture should be separated from the EEG. Eye blinking and eye movement are all out-of-control body movements that parasitize requisite brain signal results for operating a brain-computer interface (BCI).
A foetal electrocardiogram (ECG) artefact removal algorithm called speedy fixed point has been suggested [3]. In this algorithm, independent component analysis (ICA) is applied to explore the ECG. The isolated signal is renovated using principal component analysis, and then the renovated foetal EEG signal is further cleaned by wavelet technology to enhance the algorithm accomplishment. The disadvantage of this method is that the eye blinking cannot be removed completely, but just reduced. Abdullah and Zhu [4] used evolutionary SBSS to delete artefacts such as ballistocardiogram BCG, electro-oculogram EOG from EEG signals measured inside BCI. The proposed solution overcomes the problems associated with the conventional method, such as source opacity, disordered independent components and a large number of independent components. Dutta et al. [5] used ensemble empirical mode decomposition with optimization via deep learning proficiency to denoise EEG signals. Deep learning attempted to realize and tune the optimization process without the need to pretreat the EEG signals.

Yakoubi et al. [6] used extended Kalman filters (EKF) to remove white and coloured Gaussian noises from EEG recordings. This process was based on a joint Multi-Layer Perceptron (MLP) with a Kalman filter (KF) and was successful for tracking the physiological and pathological states of EEG signals with different types of artefacts, such as muscle and movement. A modification of the filtering method based on the separation between vertical and horizontal EOG channels takes them as two different reference inputs. The least mean square (LMS) is a common method used in adaptive filtering, and the recursive least square (RLS) method is used to minimize the expectancy error. The main difficulty associated with this design is the filter order and convergence factor. The RLS method is simple, fast, and the results do not require a complex calculation, but additional channels are needed to provide a reference signal, and a negative spike appears at the EOG spike. A study by Krishnaveni et al. [7], compared different types of ICA algorithms (JADE, RADICAL, Kernel-ICA, MS-ICA, SHIBBS) for EOG rejection and concluded that the RADICAL algorithm is the best algorithm to separate the EEG mixtures.

The second-order blind identification (SOBI) algorithm is used to prepare an automatic algorithm to extract EEG artefacts from EEG mixtures, and the SOBI algorithm is effective for multichannel EEG recordings. An algorithm based on SOBI and SVM by Gregory et al. [8] described the rejection of the EOG artefact. The SOBI technique was used to separate the EEG independent sources, and the SVM was used to select eye blink artefact components. SVMs are trained to identify the artefact component with high classification accuracy, but the training step is complex and requires a large number of eye blink and non-eye blink artefact-independent components.

Discrete wavelet transformation (DWT) with the adaptive predictor filter (APF) has been integrated by Zhao et al. [9] to suppress the EEG artefact, preserving the spectrum and coherence of neural activity. The algorithm is applied only to the frontal and frontal polar channels. Mannan et al. [10] proposed a combination of independent component analysis (ICA), regression and high-order statistics to identify and eliminate artefactual activities from the EEG mixture. The proposed method can identify and eliminate artefactual activities from the EEG data compared with the four methods, namely ICA, regression analysis, wavelet-ICA (wICA), and REGression-ICA (REGICA), but the proposed method is restricted to extract eye blink artefacts.

Most previous studies have used ICA, which has some limitations, including an equal number of output components and observations, source opacity, disordering of the output components, and loss of amplitude information in the output components. The use of ICA for artefact rejection poses difficulties because of the above-mentioned shortcomings.

Among these methods, Stone’s BSS can separate the source signals from the mixed signals without needing any information regarding the source signals or the mixed matrix. Rejection of eye blinking is an important research area and remains an unmet challenge.

Abdullah et al. [11] suggested a modification of Stone’s BSS based on the fast genetic algorithm (FGA), and the hybridization was used to generate and tune the optimal value of half-life \( h_\text{L} \), \( h_\text{S} \) parameters, which affect the separation process of Stone’s method by using the responses of two different linear scalar filters for the same set of signals. The fast-genetic algorithm is a powerful technique to enhance the separation process when hybridized with Stone’s blind source separation algorithms. This hybridization is applicable to clean the EEG brain signals from different types of artefacts; therefore, it is possible to further enhance the separation process by using other soft computing techniques, such as particle swarm optimization (PSO) or the artificial Bee Colony algorithm.

In this paper, an improved Stone’s BSS method is proposed to reject eye blinking from the EEG mixture. This new application of Stone’s BSS in brain signal analyses, similar to the majority of previous works based on independent component analysis, has some inherent disadvantages. In Stone’s BSS incorporating the initial vector into the particle swarm optimization (PSO) iterative algorithm, the initial vector is generated randomly. The PSO algorithm is used to gradually find the optimal value of half-life \( h_\text{short}, h_\text{long} \) to complete the separation process.

The value of \( h_\text{short} \), \( h_\text{long} \) is fixed in the conventional Stone’s BSS, typically at \( h_\text{long} \geq 100h_\text{short} \). Using PSO alone to find the solution for the blind source separation has some shortcomings, such as poor accuracy of the separation matrix \( W \) because of the random generation of the initial coefficients, and slow speed of the separation process due to the increase in size of the candidate solutions.

In the proposed algorithm, the value of \( h_\text{short}, h_\text{long} \) is gradually found to enhance the separation process. The mixture of signals will be uncorrelated when \( h_\text{short} \to 0 \) and \( h_\text{long} \to \infty \). Stone’s BSS is applied to convert the X signal to separate the independent signal, which is not completely
The EEG system is designed to measure the electrical waves that show the biological functions of the human brain by placing sensing equipment on the head surface. EEG signals are present in an unsystematic susceptible range compared with the artefacts. The drawing signals that are not originally cerebral can be described as artefacts and categorized as follows:

1. Electroencephalogram (EEG) polluted with power line noise interference;
2. Electroencephalogram (EEG) combined with eye blinking;
3. Electroencephalogram (EEG) combined with eye movement;
4. Electroencephalogram (EEG) combined with Cardiac artefacts.

A. POWER LINE NOISE ARTEFACTS
The EEG signals are often polluted with misunderstanding signals by the power line noise (LN) (50–60 Hz / AC). The line noise signals are strong references created from A/C power equipment, cable effect, and fluorescent light during the recording process. The notch filter is used to remove the artefacts because its frequency and harmonics are lower than the LN frequency, and it can delete EEG data (useful signals) between 50 and 60 Hz. Figure 1(b) displays the power line artefacts with the EEG signal.

B. ELECTROOCULALGRAM (EOG) OR OCULAR ARTEFACT (OA)
This kind of signal is generated from eye winks or eye motion. The eye movement frequency is less than 4 Hz. Blinks of the eyes are low propagation, but the movement is high. Eye blinks have a spike shape, as shown in Figure 1(c), while eye movements have a square-shaped signal, as displayed in Figure 1(d).

C. ELECTROCARDIOGRAPHY
ECG signals, also called heartbeat signals, are generated when blood vessels are under or near an electrode. The cardiac movement has a clear and huge electrical power influence on the ECG signals. Figure 1(e) shows the ECG artefacts, which appear as continual pins during the EEG recording process.

II. PROPOSED WORK DATA SET
The EEG uses electrodes connected to the scalp to receive a produced electric signal via the brain. The electrodes are positioned using the 10-20 international system, as shown in Figure 2. In the present study, two data sets are used: real EEG data and simulated EEG data using MATLAB R2018.

A. REAL EEG DATA
The brain computerized interface (BCI) device is used to measure EEG signals from the patients. The device has nine-channel electrodes and a sampling rate of 0–256 Hz.
The data collected from the BCI device were sampled at 256 Hz and have a notch total length of 2 minutes. The proposed algorithm is implemented to reject eye blinking without deleting any important data from the EEG. The ISR measures the algorithm performance by using simulated data, but it is not applicable for actual EEG data because the mixing process is unknown. Therefore, the correlation measure is used to evaluate the removal operation for the proposed algorithms. In this study, eight transmission paths are applied as shown in Figure 3, where C3, C4, O1, O2, Fp1, and Fp2 are the six electrodes used to calculate the signals from the human brain. Such electrodes are positioned on the scalp corresponding to the 10-20 system diagrams. The eye blinking artefact is clearly observed in the frontal channels (Fp1, Fp2), and it decreases with increasing distance between the electrodes and the eye. To assess face movement, vEOG and nEOG are used.

B. SIMULATED EEG DATA SET
Artificial EEG and eye blinking sources are generated in MATLAB as shown in Figure 4. Different types of artefacts and EEG signal simulation are conducted on the basis of the characteristics of each signal. Two predominant theories are commonly used to create phase-resetting theories [15], [16]. The peaks in event-related potential (ERP) signals in classical theory indicate a phasic impulse that represents the brain activity generated by testing events in one or more areas.

In phase-resetting theory, the testing case resets the phase of continuous oscillations. Rasheed [17] used the phase-resetting method to generate the EEG data. Algorithm 1 presents how a simulated EEG dataset is created.

Eye blinking is simulated using the sine function and interbreed randomly by mixing the signal to produce a mixed signal (Figure 5). The signals are combined randomly by mixing array A to create combination X.

III. PROPOSED METHOD
The proposed algorithm, called intelligent Stone’s BSS (ISBSS), is based on the hybridization between SBSS and PSO to reject eye blinking artefacts from EEG brain signals.

In general, EEG signals have two beneficial characteristics: a Gaussian likelihood density based on the central limit theorem, the level of statistical independence and temporal predictability (TP). Stone’s PSO is used as the TP measure (TPM) to separate the data into main data, blend, and speculation.

For signal, $y(k)$, the TPM is defined as follows [17, 18]:

$$F(y) = \log \frac{V_y}{U_y} - \log \frac{\sum_{k=1}^{N} (y_{\text{long}}(k) - y(k))^2}{\sum_{k=1}^{N} (y_{\text{short}}(k) - y(k))^2}$$  (1)

$$y_{\text{short}}(k) = \beta_s y_{\text{short}}(k-1) (1 - \beta_s) y(k-1)$$  (2)

$$y_{\text{long}}(k) = \beta_L y_{\text{long}}(k-1) + (1 - \beta_L) y(k-1)$$  (3)

where $N$ is the total data for $y(k)$, $\beta_s = 2^{-1/h_{\text{short}}}$, $\beta_L = 2^{-1/h_{\text{long}}}$, and $h_{\text{short}}$, $h_{\text{long}}$ are half-life variables.

The half-life $h_{\text{short}}$ of $\beta_s$ is 100 periods shorter than the half-life $h_{\text{long}}$ of $\beta_L$. These values are determined by
Eqs. (4&5) using the proposed algorithm:

\[
\begin{align*}
    h_{\text{long}} i+1 &= h_{\text{long}} i + \gamma \quad (4) \\
    h_{\text{short}} i+1 &= h_{\text{short}} i + \gamma \quad (5)
\end{align*}
\]

where \(\gamma\) is a random value, \(h_{\text{long}} i+1\) is the new \(h_{\text{long}}\) value, and \(h_{\text{short}} i+1\) is the new \(h_{\text{short}}\) value. Assuming \(\gamma(k) = w^T_k x(k)\), and \(W = [w_1, w_2, \ldots, w_n]\), according to Eq.4 and Eq.5, Eq.1 can be rewritten as follows [7]:

\[
F(y) = \frac{w_{i}^T C_{xx}^{\text{long}} w_{j}^T}{w_{i}^T C_{xx}^{\text{short}} W_{j}^T}.
\]  

where \(C_{xx}^{\text{long}}\) is a long-range covariance array (\(N \times N\)) among the signal combinations, and \(C_{xx}^{\text{short}}\) among the \(i_{th}\) and \(j_{th}\) blends, respectively, are defined as follows [7]:

\[
\begin{align*}
    C_{x_{i} x_{j}}^{\text{short}} &= \sum_{t} \left( x_{it} - x_{it}^{\text{short}} \right) \left( x_{jt} - x_{jt}^{\text{short}} \right) \quad (7) \\
    C_{x_{i} x_{j}}^{\text{long}} &= \sum_{t} \left( x_{it} - x_{it}^{\text{long}} \right) \left( x_{jt} - x_{jt}^{\text{long}} \right) \quad (8)
\end{align*}
\]

The essential purpose of Stone's algorithm is to maximize Rayleigh's proportion and create an unblended array.

Algorithm 1 Generation of Artificial EEG Signals Contaminated by Eye Blinking Using Phase Resetting

**Inputs:** frames, epochs, srate, minfr, maxfr, position, tjitter.

**Outputs:** Simulated EEG signal

**Steps:**

1. Describing the number of signal frames per trial, number of simulated trials, sampling rate of the simulated signal, minimum frequency of the sinusoid being reset, maximum frequency of the sinusoid being reset.
2. Generating the Artificial EEG according to the following:

   \[
   \text{signal} = \text{zeros}(1, \text{epochs} \times \text{frames});
   \]

   for trial = 1:epochs
   \[
   \text{wavefr} = \text{rand}(1) \times \text{(maxfr-minfr)} + \text{minfr};
   \]

   \[
   \text{iniphase} = \text{rand}(1) \times 2 \times \pi;
   \]

   \[
   \text{pos} = \text{position} + \text{round}(\text{randn}(1) \times \text{tjitter});
   \]

   for i=1:frames
   \[
   \text{if } i < \text{pos}
   \]

   \[
   \text{phase} = \text{i/srate} \times 2 \times \pi \times \text{wavefr} + \text{iniphase};
   \]

   else
   \[
   \text{phase} = (\text{i-pos})/\text{srate} \times 2 \times \pi \times \text{wavefr};
   \]

   end

   \[
   \text{signal}((\text{trial}-1)\times \text{frames}+i) = \sin(\text{phase});
   \]

   end

   End Generate.

3. Generating the eye blinking according to the following:

   \[
   \text{signal} = \text{zeros}(1, \text{epochs} \times \text{frames});
   \]

   for trial = 1:epochs
   \[
   \text{freq}=0;
   \]

   \[
   \text{range}=[(\text{trial}-1)\times \text{frames}+1:\text{trial} \times \text{frames}] ;
   \]

   for i = 1:sunmsg
   \[
   \text{freq} = \text{freq} + (4 \times \text{rand}(1));
   \]

   \[
   \text{freqamp} = \text{meanpower}((\text{ceil}(\text{freq})
   \]

   \[
   (125)) / \text{meanpower}(1);
   \]

   \[
   \text{phase} = \text{rand}(1) \times 2 \times \pi;
   \]

   \[
   \text{signal} \left( \text{range} \right) = \text{signal} \left( \text{range} \right) + \sin( (1: \text{frames}) \times \text{srate} \times 2 \times \pi \times \text{freq} + \text{phase}) \times \text{freqamp};
   \]

   end

4. Generate the artificial EEG signals contaminated by eye blinking by combining the output from step 2 and output from step 3.

5. End

The blending processes are as follows:

\[
X(k) = AS(k).
\]  

where \(X(k) = [x_1(k), \ldots, x_n(k)]^T\) is the blend data from the devices or sensing element (known), \(S(k) = [s_1(k), \ldots, s_n(k)]^T\) is the source data (unknown), \(T\) refers to...
the transpose operator, $A \in \mathbb{R}^{(n \times n)}$ is a mixture of data (unknown) and $k$ is a time indicator.

The aim of Stone’s algorithm is to retrieve $S$ from $X$ without the need to know $A$. The retrieved signals are measured by the extraction model as follows

$$Y (k) = WX (k)$$ (10)

The $h_{short}$ and $h_{long}$ parameters of Stone’s algorithm are constant values, changing the parameters will impact the separated signals directly, and the best parameters cannot be specified. The proposed method uses PSO to find the optimum $h_{short}$ and $h_{long}$ to enhance the separation process.

Algorithm 2 explains the proposed ISBSS method. In this work, instead of a constant value, PSO is used to create random optimum $h_{short}$ and $h_{long}$ parameters and tune these parameters until the ending criteria are satisfied. The proposed algorithm consists of two steps: first, obtain the initial separating matrix $W_{\text{Initial}}$ by running the original Stone’s BSS with random $h_{short}$ and $h_{long}$ parameters tuned by the PSO algorithm until the stopping criteria satisfied; second, obtain the optimum separated matrix $W_{\text{Refine}}$ by tuned $W_{\text{Initial}}$ using the PSO as a refinement process for the coefficients of $W_{\text{Initial}}$ to generate $W_{\text{Refine}}$.

**Algorithm 2 Implementation of the Major Steps for the Proposed ISBSS**

**Required:** EEG Signals C3, C4, O1, O2, Fp1, Fp2, vEOG, and nEOG.

**Steps:**

1. Initialization parameters $\omega$, $\alpha^1$, $\alpha^2$, n.
2. Generate $h_{long}$, $h_{short}$ and $W_{\text{Initial}}$ randomly.
3. Execute conventional Stone’s BSS.
4. Rearrange and calculate the fitness function to evaluate the cost of the current solution (particle $X(i)$).
5. Calculate the cost of $X(i)$ if it is less than the cost of $h_{best}(i)$ and then go to step 6; otherwise, go to step 7.
6. Update local bests ($h_{best}(i) = X(i)$), update global best, update velocities and positions.
7. Reach the stopping criterion of a maximum number of generations >25 and then go to step 8; otherwise, go to step 3.
8. Determine the optimum solution of $h_{long}$, $h_{short}$ and $W_{\text{ISBSS}}$.
9. Acquire the EEG signals.
10. End.

The execution of Stone’s algorithm starts with finding the initial separating matrix $W_{\text{Initial}}$. The PSO is used as an improvement procedure on the coefficients of $W_{\text{Initial}}$ to acquire $W_{\text{Refine}}$.

The initialisation configurations of PSO are as follows:

- fitness function $f : \mathbb{R}^n \to \mathbb{R}$;
- number of particles $n = 20 \ldots 200$;
- particle positions $x_i \in \mathbb{R}^n$, $i = 1 \ldots n$;
- particle velocities $v_i \in \mathbb{R}^n$, $i = 1 \ldots n$;
- current best of each particle $\hat{x}_i$;
- global best $\hat{g}$, and constants $\omega$, $\alpha_1$, $\alpha_2$.

For each particle $i = 1 \ldots n$,

- create random vectors $r_1, r_2$ with components in $U[0, 1]$;
- update velocities $v_i \leftarrow \omega v_i + \alpha_1 r_1^2 (\hat{x}_i - x_i) + \alpha_2 r_2^2 (\hat{g} - x_i)$;
- update positions $x_i \leftarrow x_i + v_i$;
- update local bests $\hat{x}_i \leftarrow x_i$ if $f(x_i) < f(\hat{x}_i)$;
- update global best $\hat{g} \leftarrow x_i$ if $f(x_i) < f(\hat{g})$;
- initialize the particle positions and their velocities as follows:

$$X = lower_{limit} + (upper_{limit} - lower_{limit}) \times \text{rand}(n_{particles}, m_{dimensions})$$

assert $X.shape = (n_{particles}, m_{dimensions}) V = \text{zeros}(X.shape)$ (11)

- Initialize the fitness function:

$$\text{Fit} (y) = \frac{1}{I(y) + \varepsilon} = \frac{1}{\sum_{i=1}^{n} H(y_i) - H(y_1, y_2, \ldots, y_n)}$$ (12)

where $y_1, \ldots, y_n$ is a separated signal, $H$ is signal entropy, $I(y)$ represents the mutual information computed by the concept of differential entropy between $n$ signals, and $\varepsilon$ is a constant value (0.0001).

The description of the parameter of the fitness function ($\text{Fit}$) is the key to the PSO algorithm performance. By minimizing the mutual information, $I(y)$ between the components, PSO aims to optimize the fitness function.

The mutual information theory is the most widely used method for measuring the independence between random matrices. This work, therefore, uses the mutual information method as the criterion for defining fitness functions. The mutual information between mix sources must be minimized to find the separated matrix, and the objective function refers to [19], as expressed in Equation (13),

$$I (y_i, y_j) = \sum_{i \neq j} p (y_i, y_j) \log \left( \frac{p (y_i, y_j)}{p (y_i) p (y_j)} \right) - \sum_{i \neq j} p (Wx_i, Wx_j) \log \left( \frac{p (Wx_i, Wx_j)}{p (Wx_i) p (Wx_j)} \right)$$ (13)

If $I (y_i, y_j) = 0$, then $y_i, y_j$ are independent and separated, and the fitness function can be defined as Equation (12), where:

$$\text{Fit} (y) = I (y_i, y_j), \quad y_i, y_j \in y, i \neq j$$ (14)

Additionally, regarding the concept of the maximization of the entropy of mixed signals, the maximization of entropy indicates a higher independence between signals because $I (y_i, y_j)$ is non-negative and, consequently, $H (y_i) \geq H (y_1, y_2, \ldots, y_n)$. 

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Together with the PSO algorithm, the optimum solution and separated signals can be obtained by rewriting Eq.10:

\[ y(k) = W_{\text{Refine}}x(k) \]  

(15)

The raw data are pre-processed by the centring and whitening process for simplicity. The whitening process is a linear transformation that is used for calculation simplicity by converting the obtained vector to another vector, whereby the whitened components are uncorrelated and their variance equals unity. The eigenvalue decomposition of the covariance matrix is utilized to obtain the whitening matrix [20].

The final step after extraction of the EEG artefact is to reconstruct the EEG data. The reconstruction algorithm should be used to analyse the temporal structure of the independent components \( S(t) \) and identify artefact components. The classical way set the identified artefactual components to zero, \( S_{\text{artf}}(t) = 0 \) (i.e., \( IC_6 = 0 \)), as shown in Figure 6, where the artefactual sources have been rejected and the EEG-data reconstructed as follows:

\[ \hat{x}(t) = A\hat{s}(t) \]  

(16)

where \( \hat{x}(t) \) represents the artefact-free data, \( A \) is the mixing matrix \( A=W^{-1} \), \( W \) is the un-mixing matrix and \( \hat{s}(t) \) is a new component matrix.

### IV. RESULTS AND DISCUSSION

The ISBSS algorithm is compared with the original SBSS, EFICA, FastICA, and JADE to ascertain its effectiveness, as displayed in Figure 6. The real EEG waves are possessed until the third second \( (256 \times 3 = 768) \) specimens, which are organized by the existence of eye artefacts compared with the output curve generated by other algorithms for the FP1 channel. The ISBSS algorithm is clearly superior to the other algorithms due to the removal of brain signals and isolation of eye blink artefacts.

Mixture recognition is based on the non-complex gauge method denoted the sparsity measure Eq.17, which is applied as follows [21]:

\[ \text{Sparsity}(y^{(j)}) = \frac{\max[y^{(j)}]}{\text{std}[y^{(j)}]} \log \left( \frac{\text{std}[y^{(j)}]}{\text{median}[y^{(j)}]} \right) \]  

(17)

where \( y^{(j)} = [y_{1}^{(j)}, \ldots, y_{N}^{(j)}] \) is the \( j_{th} \) ingredient, \( N \) is the sample size in the framework, \( \text{std} \) is the typical perversion, and the period indicator is \( i \).

The sparsity measure is applied to segregate the split component signal into an artefact or not. Very good rejection is obtained with the proposed algorithms of the blink artefact, showing clear isolation of the eye blink artefact with IC6 (see Figure 6 and Table 1).

Table 2 shows the relation between the artefact-reference signal and the artefact portion extracted with a blinking eye. Two methods are used to obtain an artefact-reference signal to calculate the correlation between the extracted artefacts and the artefact-reference signal; the first method is based on the channel-reference method, and the second method is based on the enhanced channel reference algorithm.
The channel reference is widely used to evaluate the performance of the eye blink artefact removal algorithms by comparing the extracted eye blink artefact with the vEOG channel. However, the signals from EOG electrodes are contaminated by another signal produced from brain or external sources [10]. For EOG artefacts, the EOG electrodes (vEOG and hEOG) are used as reference signals. For EOG electrodes (vEOG and hEOG) placed above and on the side of the left eye, a socket is used to measure the face activity. This method is controlled as follows:

\[ r_i(t) = f(q_j(t)) \quad i = 1, 2, \ldots, k \quad j = 1, 2, \ldots, l \]  

(18)

where \( i \) is the number of reference signals used, \( q \) is the recorded signal, \( j \) is the channel number, \( l \) is the total number of channels recorded, and \( f \) is the filtering process.

The enhanced channel reference algorithm is a modification of the EOG channel reference method presented in [9] based on the morphologies and relative timings of the contaminating electrodes to extract the eye blink reference signal from EEG electrodes.

The ISR measure is not applicable to real EEG data because the mixing process is unknown. Therefore, the correlation measure is used to assess the extraction process for the proposed algorithms.

The result of the simulated EEG signals shows better performance compared with the SBSS, EFICA and JADE algorithms. Figure 7 and Table 3 show the recovered signals using the ISBSS algorithm. To visually compare the results, Figure shows the FPI and FP2 recorded signals using the ISBSS, SBSS, FICA, and JADE algorithms, shifting vertically for display purposes.

Two indexes are used to check the effectiveness: carrier-to-interference ratio (CIR) and integral square error (ISE), see Table 4. Implementation of the simulated data is estimated by CIR [22] using Eq.19, where \( s(k) \) denotes the original signals,

\[
\text{CIR}_i = 10 \log \frac{E \left[ (s_i(k) - y_i(k))^2 \right]}{E \left[ s_i(k)^2 \right]} \]  

(19)

The results of the separation process are better regardless of whether the CIR measure is reduced. The results are shown for ISBSS (−72.12026 dB), and the worst value is obtained using the SBSS technique (−49.9364 dB).

The second index used to check the effectiveness is the integral square error (ISE), where

\[
\text{ISE} = \sum_{k=0}^{T} (s_i(k) - y_i(k))^2 \]  

(20)

\[
\frac{I_{\text{CIR}}}{I_{\text{ISE}}}
\]

\[
\frac{I_{\text{CIR}}}{I_{\text{ISE}}}
\]

\[
\frac{I_{\text{CIR}}}{I_{\text{ISE}}}
\]
To evaluate the effectiveness, Table 5 shows the spectral density estimation (SDE) value for the raw EEG signal, as well as two well-known BSS algorithms (JADE, EFICA) and two Stone’s BSS algorithms (SBSS, MSBSS), of which MSBSS refers to the modify stone blind source separation as presented by Abdullah [11] we use Welch’s method to estimate the SDE value. The SDE value in the proposed algorithm is less than in the other algorithms.

V. CONCLUSION

In this paper, an approach based on the hybridization between the signal processing technique and artificial intelligent algorithms is proposed. The classic Stone’s technique uses TP, which indicates that the short-term and long-term linear predictors are not novel, but tuning half-life values ($h_L, h_s$) by PSO is new. The proposed algorithm is shown to be a powerful technique for extracting eye-blinking signals from EEG brain mixtures in comparison to various algorithms, such as the original SBSS, EFICA, and JADE. ISBSS performs better than different types of BSS algorithms, as demonstrated in simulated and experimental outcomes to evaluate effectiveness. Stone’s BSS algorithm is a useful technique in medical applications to separate different types of artefacts from EEG data.

For future work, nemour artefacts maybe appear in EEG signals such as ballistocardiogram (BCG) and electromyogram (EMG) artefacts. The ISBSS is expected to be a useful algorithm to reject these artefacts. This study can be extended to reject additional types of artefacts, such as BCG and EMG, and can also be extended by the hybridisation of Stone’s BSS with another machine learning algorithm or soft computing techniques.

DATA AVAILABILITY

The data used to support the findings of this study are available on request from the author.

CONFLICT OF INTERESTS

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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