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# Comparative Analysis of Denoising Techniques for Optimizing EEG Signal Processing

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## *Abstract*

*Electroencephalogram (EEG) is a non-invasive technology widely used to record the brain's electrical activity. However, noise often contaminates the EEG signal, including ocular artifacts and muscle activity, which can interfere with accurate analysis and interpretation. This research aims to improve the quality of EEG signals related to concentration by comparing the effectiveness of two denoising methods: Independent Component Analysis (ICA) and Principal Component Analysis (PCA). Using commercial EEG headsets, this study recorded Alpha, Beta, Delta, and Theta signals from 20 participants while they performed tasks that required concentration. The effectiveness of the denoising technique is evaluated by focusing on changes in standard deviation and calculating the Percentage Residual Difference (PRD) value of the EEG signal before and after denoising. The results show that ICA provides better denoising performance than PCA, as reflected by a significant reduction in standard deviation and a lower PRD value. These results indicate that the ICA method can effectively reduce noise and preserve important information from the original signal.*

***Keywords:*** *Electroencephalogram (EEG), Independent Component Analysis (ICA), Principal Component Analysis (PCA), Percentage Residual Difference (PRD).*

## 1. Introduction

The electroencephalogram (EEG) has become a tool for understanding the complex mechanisms of the human brain and provides essential insights into neuroscience and clinical applications[1], [2], [3]. As a non-invasive technique, EEG allows researchers and clinicians to monitor brain electrical activity with high temporal resolution, which is essential for studying various aspects of brain function, including, but not limited to, cognition, emotion, sensory processing, and motor control [4]. The utility of EEG extends from basic research to clinical applications, including diagnosis of neurological disorders, sleep monitoring, and even as a brain-computer interface in neuroprosthetic technology [5]. However, the resulting EEG signal is often contaminated by noise, which can reduce the quality of the data obtained, thereby limiting its ability to provide accurate and reliable information [6], [7]. Noise in EEG signals can originate from various factors, including physical artifacts such as eye blinks, eye movements, and muscle contractions, as well as external sources such as electromagnetic interference from electrical equipment or signal fluctuations from the recording device [8], [9]. In the clinical setting, this noise can be further complicated by patient movement, variations in scalp conductivity, and pharmacologic influences. In previous research, techniques have been carried out to overcome data noise, such as using the Ensemble Empirical Mode Decomposition (EEMD)-Independent Component Analysis (ICA), EEMD-Canonical Correlation Analysis (CCA) method, and the Wavelet Threshold Denoising method. [10], [11]. Among the denoising techniques used in previous research, the method Independent Component Analysis (ICA) and Principal Component Analysis (PCA) have shown promising results in denoising [12], [13]. ICA works by separating mixed EEG signals into independent components, and PCA reduces the dimensionality of the data while preserving the most significant variance [14]. However, despite their effectiveness, there has yet to be a clear consensus on which method is superior in specific contexts, such as when performing tasks requiring high concentration. Therefore, this study sought to compare these two techniques to optimize EEG signal processing, especially during tasks requiring concentration. It uses commercial equipment such as the Muse 2, which in the future can be used as an economical brain wave recording device and produces brain wave data needed to analyze a person's concentration or level of fatigue. The EEG tool used in this research has standardized measurements that can be calibrated to produce appropriate data for each signal before signals containing noise from muscle movements in the head area or other noise can be subjected to a signal denoising process. Even though there has previously been data recording brain wave data, the existing data has different characteristics from the data needed in this research, both in the form of essential data required to analyze concentration, especially the economical devices used. This research will later contribute to producing the best denoising standards that can work on economical recording devices that can be widely used. This study used a commercial EEG headset to record signals from 20 respondents performing cognitive tasks to assess their concentration. A small dataset is used in this research because EEG data is susceptible, so it requires very controlled data collection. Researchers also need to ensure that the data collected from each subject is consistent and of high quality, which is often easier to do in studies with smaller samples. Based on previous research, many EEG studies are designed to answer particular research questions or to look at detailed neurological phenomena using only participant data of 21, 14, 10, and even four respondents, thereby reducing the need for extensive data samples because the focus is on highly controlled and detailed observations of specific phenomena, rather than on generalizing findings to a broader population [15], [16], [17], [18]. This study evaluated how each denoising technique can reduce the Percentage Residual Difference (PRD) and Standard Deviation error metrics. A reduction in these error metrics would indicate an improvement in the quality of the resulting signal, which could directly contribute to more accurate analysis and more reliable interpretation.

## 2. Research Methods

In its implementation, this research needs to carry out several processes to determine which denoising method is the best and most appropriate for denoising recorded brain wave data. The first stage of this research was to record the brain waves of 20 participants and then label the brain wave data. The participants in this research were a group of productive people aged 19 to 33 years. Of the 20 respondents, 8 were men and 12 were women. The aim of taking samples from this productive group is to analyze this data to detect worker fatigue. After the labeling, the denoising process uses the ICA and PCA methods. After denoising using the three methods, the next step is to calculate the standard deviation of the original recording and brain wave recording after denoising. The following is a detailed depiction of the process flow of this research.

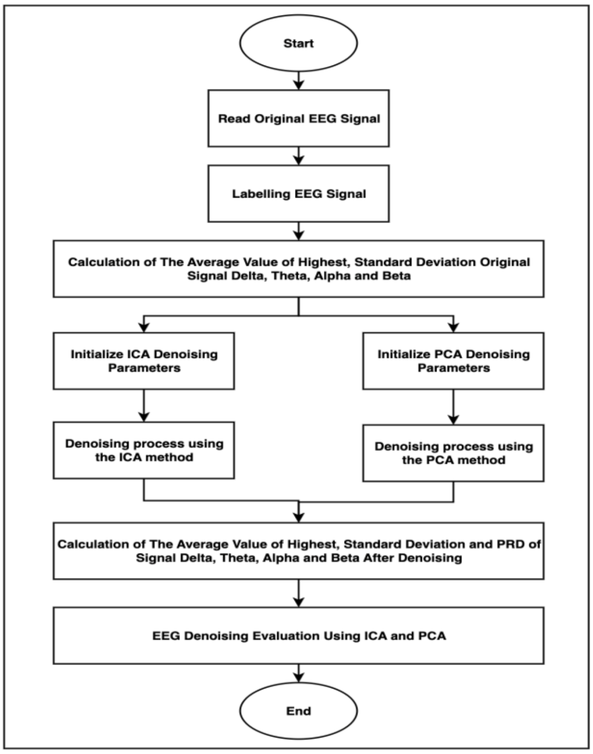


**Figure 1.** Research Flow

### 2.1. Data Collection

In this research, the EEG data collection process was carried out by twenty participants. Each of them underwent a brain wave data recording session that lasted an average of five minutes. During the recording period, participants were presented with tasks designed to induce and maintain high concentration levels. This activity is intended to stimulate brain activity, which can produce quality EEG signals that are representative of the desired cognitive state. The device used for recording was the EEG Muse 2 headset, which was chosen because of its ability to detect and record various brain waves with high accuracy. This headset has sensors that can capture the brain's electrical signals and convert them into digital data, including Alpha, Beta, Delta, and Theta signals. The Muse 2 device is light and portable, making it easier for researchers and participants to use the headset in various conditions. This type of headset will also make it possible to develop a brainwave reading system for fatigue detection for air traffic controllers, drivers, and office workers. Each recording session is carried out under controlled conditions to minimize external interference that could affect data quality. The data obtained from the recording is then processed using denoising techniques, which will be tested in this research. This denoising process is essential to remove unwanted noise components and ensure that the analyzed signal faithfully represents the brain activity associated with the cognitive task. The results of the analysis can be relied on to provide deeper insight into the cognitive mechanisms being studied.

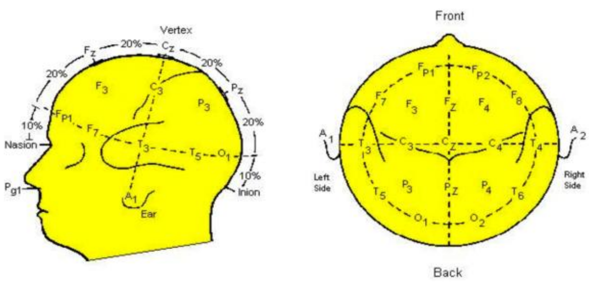


**Figure 2.** Point of Brainwave Location

Figure 2 depicts the EEG 10-20 electrode placement system, the international standard method for placing EEG electrodes on the scalp [19]. In the Muse device that researchers use, there is a simplification in the position of the electrodes for recording without eliminating the primary function of recording Alpha, Beta, Delta, and Theta signals. This device's sensors are two on the forehead (AF7 and AF8 in 10-20 notation), which measure frontal activity related to executive function, concentration, and relaxation. Apart from that, two additional sensors are located in the ear (TP9 and TP10 in 10-20 notation), which are used as references or ground.

## 2.2. Brainwave Frequency Labelling

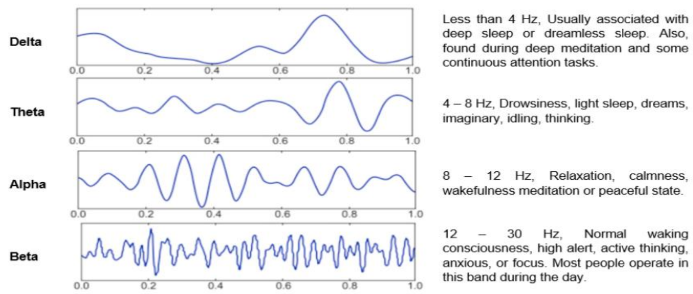


**Figure 3.** Explanation of the Function of Each EEG Signal

After recording, the EEG data collected from each respondent is saved in CSV format. This format facilitates subsequent data analysis using various signal-processing tools and techniques. Before moving on to a more in-depth analysis stage, this initial stage focuses on verifying the recorded data. This verification includes checking for the presence and quality of the four main brainwave signal categories: Alpha, Beta, Delta, and Theta. Each category represents a different frequency range associated with different mental states.

In Figure 3, Delta waves are associated with very deep sleep stages, meditation, and brain recovery processes. Delta signals mark brain activity during unconsciousness or dreamless sleep. Theta Waves can indicate light to moderate sleep, relaxation, and creativity. Theta signals often appear when individuals are daydreaming or on the verge of sleep. Alpha Waves represent a relaxed but conscious state, frequently occurring when the eyes are closed, and a person rests without sleep. Alpha waves are considered necessary for brain coordination and stress-free awareness. Beta waves are associated with active consciousness, concentration, alertness, and cognitive activity. Beta waves dominate when awake, alert, and actively processing information [20]. Each recorded EEG signal will be assessed to ensure the detected frequencies match the pre-set parameters. This will ensure data integrity for further analysis and confirm that the EEG headset can capture the spectrum of brain activity required for this study. This verification step is crucial to validate that the EEG data collected reflects brain activity according to the cognitive task given to the respondent. The implementation of brain wave frequency labeling will allow research to proceed to the analysis stage with data that has been organized and verified, ready to be processed through more complicated denoising and comparative analysis techniques.

## 2.3. EEG Signal Denoising

EEG signal denoising is an essential stage in neurological data processing, which aims to reduce noise and improve the quality of recorded brain signals [21], [22]. In this study, the denoising step became the main focus after data collection, where the EEG signals collected from respondents were evaluated to ensure that relevant signals such as Alpha, Beta, Delta, and Theta were detected clearly and free from unwanted distortion. Noise that commonly affects EEG recordings can originate from muscle or electromagnetic activity, which can cause artifacts that can potentially interfere with data analysis. To purify the EEG signal from these interferences, we apply a denoising method consisting of Independent Component Analysis (ICA) and Principal Component Analysis (PCA). ICA separates independent signal sources from noise, and PCA reduces the data to principal components that reflect the most significant variability. The denoising results will then be analyzed to ensure that the quality of the EEG signal has been improved and is ready for further analysis by reducing unwanted signal variability and preserving the essence of the brain signal. An effective denoising process aims to produce cleaner EEG data to more accurately detect brain activity related to the cognitive task under study.

### 2.4. Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is a sophisticated method that functions on the assumption that the observed signal is a linear mixture of several unknown and statistically independent signal sources [13],[23],[24],[25]. In the context of EEG, this assumption is particularly relevant because EEG often aggregates many different sources of brain activity, including both beneficial neuronal activity and undesirable artifacts [26]. ICA operates by decomposing overlapping EEG signals into independent components representing different sources. Components correlating with artifacts, such as eye movements or heart rate, can be identified and removed [25]. The following are the steps for denoising EEG data using the ICA method. The first step is to standardize EEG data by calculating the average value (μ) and standard deviation (σ) and then applying it to the data standardization formula.

$$x' = \frac{x-\mu}{\sigma} \tag{1}$$

The $x$ value is the original value, and $x'$ is the result of data standardization. The next step is to calculate the capacity matrix using a formula.

$$C = \frac{1}{N-1} \times (X-\bar{X})^T (X-\bar{X}) \tag{2}$$

$X$ is the standardized EEG data matrix, and $\bar{X}$ is the average of the columns in $X$. Next, calculate eigen decomposition by calculating the eigenvalue ($\lambda$) and eigenvector ($v$) from the covariance matrix.

$$C: Cv = \lambda v \tag{3}$$

In the following process, independent component selection and EEG signal reconstruction are carried out to obtain the signal used.

$$X_{\text{reconstructed}} = S_{\text{selected}} \times A^T \tag{4}$$

The value ($S_{\text{selected}}$) is the independent component selected, and ($A$) is the mixing matrix. The result of this method is to determine the composition, which is assessed as an artifact from reconstructed data

### 2.5. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a statistical technique used to reduce the dimensionality of data while retaining as much information as possible [27], [28]. In the context of EEG, PCA facilitates denoising by reducing redundancy and noise in the data. This method converts the original signal into a new set of uncorrelated components called principal components. These principal components are ranked based on how much data variance they capture. PCA removes noise while preserving essential signal features by eliminating components that contribute little to the total variance. To normalize data using PCA, start by standardizing the data, calculating the compariness matrix, and calculating eigendecomposition using the same formula as the calculation using the ICA method. The next step of the PCA method is to carry out principal selection by selecting ($k$) eigenvectors with the largest ($k$) eigenvalues to form a transformation matrix ($V_k$) and then transform the data into principal component space using a formula.

$$Y = X \times V_k \tag{5}$$

The Y value represents EEG data in principal component space, which is then continued by reconstructing the data using the following formula.

$$X_{\text{reconstructed}} = Y \times V_k^T \tag{6}$$

Components with low variance (small eigenvalue) are considered noise and are not included in the reconstruction.

### 2.6. Evaluation Method

At the evaluation stage, evaluation based on standard deviation and Percentage Residual Difference (PRD) is used. Evaluation based on standard deviation helps measure the effectiveness of denoising techniques in reducing variability and noise in EEG signals, with a decrease in standard deviation values indicating an increase in signal quality [29], [30]. In the context of EEG denoising, standard deviation can be used to measure variation or noise in the EEG signal. The general formula for standard deviation is.

$$\sigma = \sqrt{\frac{1}{\mathrm{N}-1}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{7}$$

Where:
- $\sigma$ is the standard deviation.
- $N$ is the number of samples in the signal.
- $x_i$ is the value of the sample in the signal.
- $\mu$ is the average (mean) of these samples.

Percentage Residual Difference (PRD) is a measure used to evaluate the quality of a denoised signal compared to the original signal [30], [31]. The formula for calculating PRD is.

$$\mathrm{PRD} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - y_i)^2}{\sum_{i=1}^{N} x_i^2}} \times 100\% \tag{8}$$

Where:
- $x_i$ is the original signal.
- $y_i$ is the denoised signal.
- $N$ is the number of samples in the signal.

These two methods allow the identification of the most optimal denoising techniques based on their ability to reduce noise and maintain signal accuracy.

## 3. Result and Discussion

This research compares denoising methods to improve the quality of the EEG signals recorded from each participant. As explained previously, the denoising methods used are the Independent Component Analysis (ICA) and Principal Component Analysis (PCA) methods. In the first step, researchers will use each technique to denoise each brain wave recording. Figure 4 is an example of a graphical comparison of original and denoised brain wave data using the ICA method.

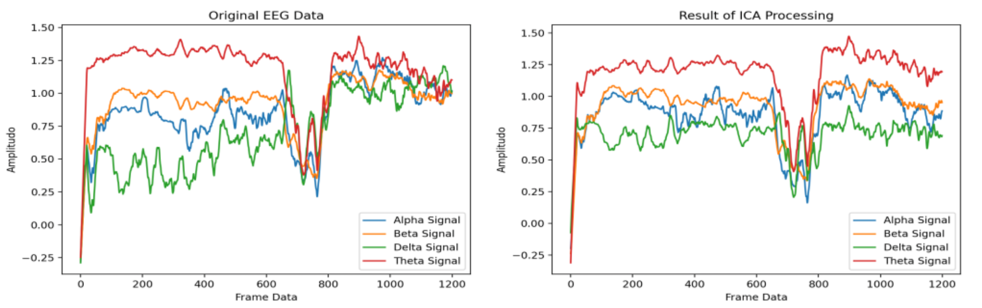


**Figure 4.** Comparison of Denoising Results Using the ICA Method

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Figure 4 shows a change in the density of brain wave data produced before and after denoising. At this stage, the data from 20 participants will be denoised first, and then the average data density will be found using the standard deviation and PRD methods. A lower PRD indicates that the denoising process can retain most of the original signal from the brain wave recording.


**Figure 5.** Comparison of Denoising Results Using PCA

Figure 5 shows the result of EEG signal denoising using the PCA method. The graphic image shows a difference in density between before and after the denoising process.

**Table 1.** Average Value of Original EEG Recorded Signals

| EEG Signal | Max Value Signal | Mean Value Signal | Standard Deviation |
|---|---|---|---|
| Alpha Signal | 1,2066 | 0,6156 | 0,2162 |
| Beta Signal | 1,0055 | 0,5718 | 0,1793 |
| Delta Signal | 1,4565 | 0,6470 | 0,2536 |
| Theta Signal | 1,4060 | 0,8196 | 0,2230 |

In the subsequent analysis process, the average value for each method is calculated for all denoising data to represent the method's effectiveness in denoising EEG signals. The following is a table of average denoising calculation results for each method used based on standard deviation and PRD values from brain wave recording data from 20 participants.

**Table 2.** Average Denoising Value Using the ICA Method

| EEG Signal | Max Value Signal | Mean Value Signal | Standard Deviation | PRD |
|---|---|---|---|---|
| Alpha Signal | 1,1975 | 0,6156 | 0,1630 | 17,8067 |
| Beta Signal | 1,0172 | 0,5718 | 0,1606 | 19,4182 |
| Delta Signal | 1,3478 | 0,6470 | 0,2195 | 18,1650 |
| Theta Signal | 1,3592 | 0,8196 | 0,2018 | 12,4769 |

Based on Table 1 using the ICA method, the signal's deviation value has decreased from the original EEG signal, for example, the Alpha signal, which initially had a standard deviation of 0.2162 to 0.1630.

**Table 3.** Average Denoising Value Using PCA Method

| EEG Signal | Max Value Signal | Mean Value Signal | Standard Deviation | PRD |
|---|---|---|---|---|
| Alpha Signal | 1,2994 | -0,8266 | 0,1639 | 112,6961 |
| Beta Signal | 0,6044 | 0,9150 | 0,1706 | 121,9211 |
| Delta Signal | 0,2818 | 0,5672 | 0,2451 | 100,1317 |
| Theta Signal | 0,1481 | -1,2045 | 0,2263 | 100,1891 |

In testing using the PCA method, the standard deviation value decreased from the actual original signal value of 0.2536 on the Delta signal to 0.2451 after the denoising process. For more details regarding significant differences in denoising results, table 4 below will explain which method produces the lowest data variation and can maintain the original data from the original signal after denoising the EEG data.

**Table 4.** Comparison of EEG Denoising Methods

| EEG Signal | ICA Denoising | | PCA Denoising | |
|---|---|---|---|---|
| | PRD | Standard Deviation | PRD | Standard Deviation |
| Alpha Signal | 17,8067 | 0,1630 | 112,6961 | 0,1639 |
| Beta Signal | 19,4182 | 0,1606 | 121,9211 | 0,1706 |
| Delta Signal | 18,1650 | 0,2195 | 100,1317 | 0,2451 |
| Theta Signal | 12,4769 | 0,2018 | 100,1891 | 0,2263 |

Table 4 depicts the lowest standard deviation values obtained using the ICA method. This low standard deviation result shows that the ICA method reduces data variations to eliminate data noise, which can interfere with the subsequent analysis process of brain waves. This low value represents all signals that underwent a denoising process, where the comparison of the standard deviation value of the Delta signal from the ICA method is 0.2195, and the PCA method is 0.2451. Likewise, with the values of the Beta, Delta, and Theta signals, the standard deviation value using the ICA method has the lowest value compared to other methods. Furthermore, the evaluation of the denoising method using PRD and the ICA method has a better value than the PCA method, and this can be seen from the comparison of the ICA PRD value, which is smaller than the PCA value. For example, the PRD evaluation of the Alpha signal using ICA has a value of 17.8067 and PCA 112.6961. A smaller PRD value indicates that the method can maintain the value of the original signal after the denoising process.

## 4. Conclusion

Based on comparative research on denoising methods that can be used to remove noise data from brain waves, the ICA and PCA methods can generally be used to remove noise data from brain waves or EEG data recordings. However, when viewed from the denoising evaluation using the standard deviation value, the ICA method has the lowest value compared to the PCA method. For example, the standard deviation value for the Beta signal in ICA is 0.1606, and PCA is 0.1706, so it can be relied on to reduce noise in EEG data. This low standard deviation value can reduce data variations caused by participants' facial or head muscle movements when recording data. Apart from that, based on evaluation with the PRD method, the ICA method has a lower value than PCA. For example, the ICA value is 17.8067 for the Alpha signal, and the PCA is 112.6961. A low PRD value indicates that the denoising method can maintain the original signal value after denoising.

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