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Improving baseline reduction for emotion recognition based on electroencephalogram signals

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ABSTRACT

The baseline reduction method has been widely used to define electroencephalogram (EEG) signal patterns. However, because the baseline signal in this approach contains artifacts, the baseline reduction approach cannot perform optimally. As a result, decreasing artifacts in the baseline signal is critical. The mean, Gaussian, and Savitzky-Golay filters will be compared in this study to minimize artifacts in the baseline signal. Three secondary datasets are utilized to evaluate these approaches' capacity to remove artifacts. These three strategies are also tested with the convolution neural network classification algorithms. When applied to the dataset for emotion analysis using physiological signals (DEAP) and a dataset for multimodal research of affect, personality traits, and mood on individuals and groups (AMIGOS) datasets, the mean filter can increase baseline reduction performance based on twenty-four test scenarios. On the data readiness for machine learning research (DREAMER) dataset, however, the Gaussian filter is preferable. The relative difference approach was employed in this study's baseline reduction process to generate EEG signal patterns that are easy to recognize throughout the classification phase, which impacts increasing accuracy.

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1. INTRODUCTION

Humans' emotional responses to interpersonal communication are critical psychological processes [1]. Emotional responses in each quadrant describe human performance and mental health [2]. Numerous attempts have been made to improve the accuracy of emotion recognition based on electroencephalogram (EEG) signals, such as deep learning, machine learning, and dataset balancing [3]–[6]. However, a wide range of other factors, such as each participant's characteristics, level of cognitive ability, and sex, can generate the difference in EEG signal patterns. This difference in EEG signal patterns affects emotion recognition accuracy [7]. A baseline reduction technique has been researched to solve this problem [8]. By using the average value of the baseline signal characteristics, the baseline reduction approach reduces the trial signal characteristics [7]–[9].

However, recording baseline EEG signals free from internal and external disruptions is challenging [3], [10], [11]. Electrooculogram (EOG), electrocardiogram (ECG), electromyogram (EMG), as well as participants' emotional reactions when they are in a calm condition, can all cause internal disturbances to EEG signals [11], [12]. The recording of the baseline EEG signal may also be disturbed by electricity at each electrode [3], [10], [11]. These disturbances may prevent the baseline reduction strategy from functioning at its best. Eliminating interference from the baseline EEG readings is crucial for solving these issues. The smoothing method can reduce the disturbances/artifacts in the baseline EEG signal by making the amplitude smoother [13]. Numerous smoothing approaches, such as the mean, Savitzky-Golay, and Gaussian filters, were used to reduce the artifact in the previous study. These three smoothing techniques have lower mean squared error (MSE) values and calculation times [13]. In earlier research, the smoothing method was not applied to emotion recognition to improve baseline reduction performance.

Based on studies from previous research, two contributions are proposed in this research: i) investigates the effects of applying three smoothing methods to the baseline signal for the baseline reduction process. While previous research has explored the impact of applying baseline reduction, it has not studied the effect of baseline reduction with a baseline signal that has been smoothed; ii) determines the best smoothing method based on the accuracy values for recognizing four and two emotion classes. The smoothed baseline EEG signal is expected to maximize the baseline reduction strategy, resulting in high accuracy in emotion recognition.

2. METHOD

The effectiveness of the baseline reduction approach was optimized by choosing the best smoothing methods. The relative difference method was the foundation for the baseline reduction procedure used in this investigation [8]. Furthermore, the classification strategy in this work used the convolutional neural networks (CNN) method, while the feature extraction and representation processes used the differential entropy (DE) and 3D cube methods [7], [8]. This stage involves segmentation, eliminating artifacts from the baseline EEG data, and decomposition. Based on the contributions proposed in this research (orange rectangle), the process of an emotion recognition model based on EEG signals can be described as shown in Figure 1.

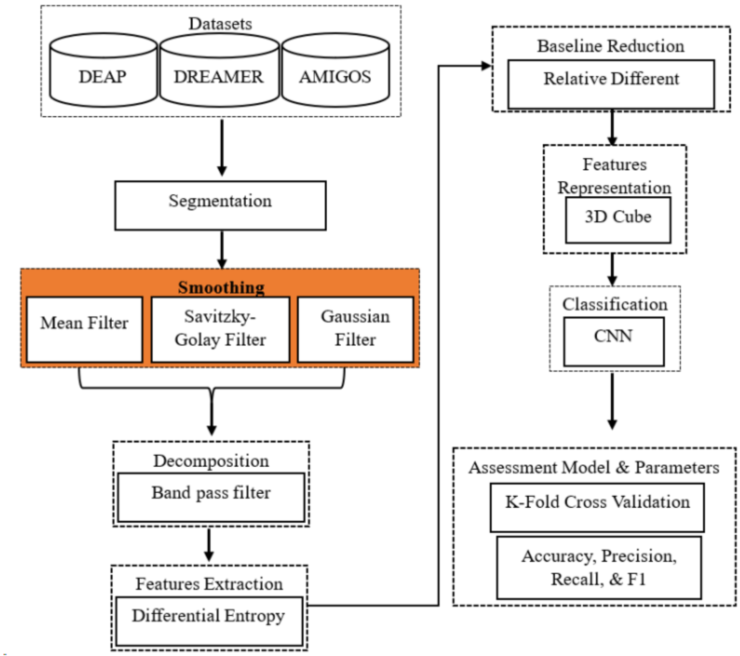

Figure 1. Emotion recognition based on EEG signal process

2.1. Emotion dataset

Preparing an EEG signal-based emotion dataset is essential to test the proposed contribution in this research. This research uses three public datasets: the dataset for emotion analysis using physiological signals (DEAP), data readiness for machine learning research (DREAMER), and a dataset for multimodal research of affect, personality traits and mood on individuals and groups (AMIGOS). These three datasets have different data characteristics, such as the number of channels used, EEG equipment, participants, and recording scenarios. So, by using these three datasets, it is hoped that we will get an appropriate smoothing method to improve baseline reduction performance and impact increasing the accuracy of emotion recognition.

2.2. Segmentation

The EEG signal is divided into two pieces throughout the segmentation process: a baseline and a trial signal. The baseline signal was an EEG reading representing the subjects' neutral state [14], [15]. The baseline signal was captured when individuals were calm and free of internal and external artifacts. The EEG signal used in the trial signal indicated the subjects' emotional responses. The baseline signals in the DEAP dataset were present for the first three seconds, while the trial signals were present for four through sixty-three seconds. In DREAMER and AMIGOS, the baseline signal lasts for the first five seconds, while the trial signal lasts for the following six seconds [16]–[18]. On DEAP, DREAMER, and AMIGOS, the EEG signal data was sampled at 128 Hz every second. There were 32 channels in the DEAP dataset. There are 14 channels in the DREAMER and AMIGOS datasets [16]–[18]. The DEAP dataset's Fp1 channel's three-second baseline signal data is shown in Table 1. The three seconds of baseline signals are displayed in Table 1. The DEAP data collection trial signal segment runs from four to sixty-three seconds (385 Hz to 8064 Hz).

Table 1. The DEAP dataset's baseline signal segments data takes three seconds

Sampling rate (Hz)	Baseline signal (x_i)
1	x_1
…………	…………
384	x_{384}

2.3. Process of smoothing the baseline signal

This procedure is the study's critical contribution. This study will examine three smoothing methods to eliminate interference in the baseline signal: the mean filter, the Savitzky-Golay filter, and the Gaussian filter [19]. The best of the three approaches was chosen based on the resulting emotion recognition accuracy value. The smoothing procedure for the mean filter method begins from the first sampling rate in the baseline signal data (1 Hz). In 1 second, the EEG signal will produce 128 sampling values. The smoothing process for the Fp1 channel in the DEAP dataset is illustrated in Table 2.

Table 2. Illustration of the smoothing process for the DEAP dataset using the mean filter method on the baseline signal

Sampling rate (Hz)	Baseline signal (x_i)	Mean filter (z_i)
1	x_1	$z_1 = \frac{0 + x_1 + x_2}{2 * 1 + 1}$
………	………	…………………………
384	x_{384}	$z_{384} = \frac{x_{383} + x_{384} + 0}{2 * 1 + 1}$

In addition to analyzing the mean filter method for smoothing the baseline signal, this study also studies the Savitzky Golay filter approach. The smoothing process for the Fp1 channel in the DEAP dataset is illustrated in Table 3. Finally, as indicated in Table 4, this study investigated the Gaussian filter approach for smoothing the baseline signal. The smoothing process for the Fp1 channel in the DEAP dataset is illustrated in Table 4. According to Tables 2 to 4, the DEAP data set's baseline signal smoothed z_j for three seconds has a 384 sampling rate. The z_j values in the DREAMER and AMIGOS datasets are 640 sample rates or 5 seconds.

Table 3. Depicts the smoothing procedure for the DEAP dataset using the Savitzky Golay filter technique on the baseline signal

Sampling rate	Baseline signal (x_i)	Savitzky Golay filter (z_i)
1	x_1	$z_1 = \frac{1}{35}(-3x_{j-2} + 12x_{j-1} + 17x_j + 12x_{j-1} - 3x_{j+2})$
…	….	……………………………………………………
384	x_{384}	$z_{384} = \frac{1}{35}(-3x_{j-2} + 12x_{j-1} + 17x_j + 12x_{j-1} - 3x_{j+2})$

Table 4. The smoothing procedure for the DEAP dataset is illustrated using the Gaussian filter method on the baseline signal

Sampling rate (Hz)	Baseline signal (x_i)	Gaussian filter (z_i)
1	x_1	$z_1 = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(x_1-\mu)^2}{2\sigma^2}}$
…….	……..	……………………
384	x_{384}	$z_{384} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(x_{384}-\mu)^2}{2\sigma^2}}$

2.4. Decomposition

This process was carried out for all channels for both baseline and trial EEG signals [7]. Table 5 illustrates the decomposition process of the EEG baseline signal for the Fp1 channel. In the DEAP dataset, 3 seconds of baseline signals (384 Hz sampling rate) were decomposed into four frequency bands for each channel [20]. The trial signal decomposition process was also carried out on the Fp1 channel, as illustrated in Table 6. In Table 6, 60 seconds of trial signals (7,680 Hz sampling rate) are decomposed into four frequency bands and each channel in one experiment (from 40 experiments in the DEAP dataset).

Table 5. Frequency band decomposition process for baseline signals on the DEAP dataset

Frequency band	*Baseline* signal		
	z_1	…..	z_{384}
Theta	z_1Theta	…..	z_{384}Theta
Alpha	z_1Alpha	…..	z_{384}Alpha
Beta	z_1Beta	…..	z_{384}Beta
Gamma	z_1Gamma	…..	z_{384}Gamma

Table 6. Decomposition process for 60 seconds of trial signals on the DEAP dataset

Frequency band	Trial signal		
	x_{385}	…..	x_{8064}
Theta	x_{385}Theta	…..	x_{8064}Theta
Alpha	x_{385}Alpha	…..	x_{8064}Alpha
Beta	x_{385}Beta	…..	x_{8064}Beta
Gamma	x_{385}Gamma	…..	x_{8064}Gamma

2.5. Feature extraction

The feature extraction process is carried out to obtain relevant EEG signal features. The feature extraction process is performed every second (128 Hz sampling rate) in each frequency band for baseline and trial signals. The feature extraction process in this research uses the DE method [7], [8]. Based on this formula the feature extraction process for the baseline signal on channel Fp1 can be illustrated in Table 7.

Table 7. Illustration of the feature extraction process for baseline signals on the DEAP dataset

Frequency band	Sampling rate (Hz)			Feature values	Second
Theta	z_1Theta	…	z_{128}Theta	h_1(Theta)	1
Alpha	z_1Alpha	…	z_{128}Alpha	h_1(Alpha)	1
Beta	z_1Beta	…	z_{128}Beta	h_1(Beta)	1
Gamma	z_1Gamma	…	z_{128}Gamma	h_1(Gamma)	1
Theta	z_{129}Theta	…	z_{256}Theta	h_2(Theta)	2
Alpha	z_{129}Alpha	…	z_{256}Alpha	h_2(Alpha)	2
Beta	z_{129}Beta	…	z_{256}Beta	h_2(Beta)	2
Gamma	z_{129}Gamma	…	z_{256}Gamma	h_2(Gamma)	2
Theta	z_{257}Theta	…	z_{384}Theta	h_3(Theta)	3
Alpha	z_{257}Alpha	…	z_{384}Alpha	h_3(Alpha)	3
Beta	z_{257}Beta	…	z_{384}Beta	h_3(Beta)	3
Gamma	z_{257}Gamma	…	z_{384}Gamma	h_3(Gamma)	3

Based on Table 7, the baseline signal will produce three DE features values for each channel and frequency band in one experiment. Further, the process of extracting experimental signal features on the *Fp1* channel can be illustrated in Table 8. Based on Table 8, the trial signal will produce 60 DE features for each channel and frequency band in one experiment.

Table 8. Illustration of the feature extraction process for trial signals on the DEAP dataset

Frequency band	Sampling rate (Hz)			Feature values	Second
Theta	$x_{385}Theta$	.....	$x_{513}Theta$	$h_4(Theta)$	4
Alpha	$x_{385}Alpha$	.....	$x_{513}Alpha$	$h_4(Alpha)$	4
Beta	$x_{385}Beta$	.....	$x_{513}Beta$	$h_4(Beta)$	4
Gamma	$x_{385}Gamma$	.....	$x_{513}Gamma$	$h_4(Gamma)$	4
…….	…….	.....	…….	…….	…….
Theta	$x_{7936}Theta$	.....	$x_{8064}Theta$	$h_{63}(Theta)$	63
Alpha	$x_{7936}Alpha$	.....	$x_{8064}Alpha$	$h_{63}(Alpha)$	63
Beta	$x_{7936}Beta$	.....	$x_{8064}Beta$	$h_{63}(Beta)$	63
Gamma	$x_{7936}Gamma$	.....	$x_{8064}Gamma$	$h_{63}(Gamma)$	63

2.6. Baseline reduction

The baseline reduction process continues after the baseline and trial signal feature values are obtained. This process aims to produce feature values from trial signals that can characterize participants' emotional reactions so emotions can be classified more accurately [7], [21]. This research will examine the relative difference method for the baseline reduction process. This method is most appropriate for characterizing different EEG signal patterns from each participant. The formula for the relative difference method can be presented in (1) [7]–[9]:

$$Final_j(X) = \frac{(Exper_j(X)}{BaseMean(X)} \tag{1}$$

The average value of the DE (BaseMean) feature on the baseline signal is calculated as an initial stage. The following is an illustration of the calculation process for the average DE feature value for each frequency band in one EEG channel on DEAP:

$$mean\_h(Theta) = \frac{(h_1(Theta)+h_2(Theta)+h_3(Theta))}{3}$$

$$mean\_h(Alpha) = \frac{(h_1(Alpha)+h_2(Alpha)+h_3(Alpha))}{3}$$

$$mean\_h(Beta) = \frac{(h_1(Beta)+h_2(Beta)+h_3(Beta))}{3}$$

$$mean\_h(Gamma) = \frac{(h_1(Gamma)+h_2(Gamma)+h_3(Gamma))}{3}$$

The mean value obtained is then used for the baseline reduction process for the trial signal. Table 9 presents the baseline reduction process using the relative difference method for one channel in one experiment on the DEAP dataset.

Table 9. Illustration of baseline reduction calculations using the relative difference method on the DEAP dataset

Frequency	Illustration of the calculation of the relative difference method
Theta	$Final\_h_4(Theta) = \frac{h_4(Theta)}{mean\_h(Theta)}$
Theta	$Final\_h_{63}(Theta) = \frac{h_{63}(Theta)}{mean\_h(Theta)}$
Alpha	$Final\_h_4(Alpha) = \frac{h_4(Alpha)}{mean\_h(Alpha)}$
Alpha	$Final\_h_{63}(Alpha) = \frac{h_{63}(Alpha)}{mean\_h(Alpha)}$
Beta	$Final\_h_4(Beta) = \frac{h_4(Beta)}{mean\_h(Beta)}$
Beta	$Final\_h_{63}(Beta) = \frac{h_{63}(Beta)}{mean\_h(Beta)}$
Gamma	$Final\_h_4(Gamma) = \frac{h_4(Gamma)}{mean\_h(Gamma)}$
Gamma	$Final\_h_{63}(Gamma) = \frac{h_{63}(Gamma)}{mean\_h(Gamma)}$

2.7. Feature's representation

The feature values of the trial signal reduced in the baseline reduction process are represented using the 3D cube method. Feature representation using the 3D cube is based on the international system 10-20 standard for channel placement on the scalp. The international 10-20 system maps the spatial information between channels representing EEG signal features to a 9×9 matrix. The 9×9 matrix describes the position of channel placement in the head. Figure 2 represents DE features mapped into a 9×9 matrix [3], [7]. The values of $Final\_h_4(Theta)$, $Final\_h_4(Alpha)$, $Final\_h_4(Beta)$, and $Final\_h_4(Gama)$ or channels *Fp1* to *O2* are presented in four 9×9 matrix. The 9×9 matrix represents theta, alpha, beta, and gamma frequencies. Then, these four matrices are combined into one cube called the 3D cube. The first 3D cube represents 1 second of EEG signal feature data for all channels and four frequency bands, as shown in Figure 2.

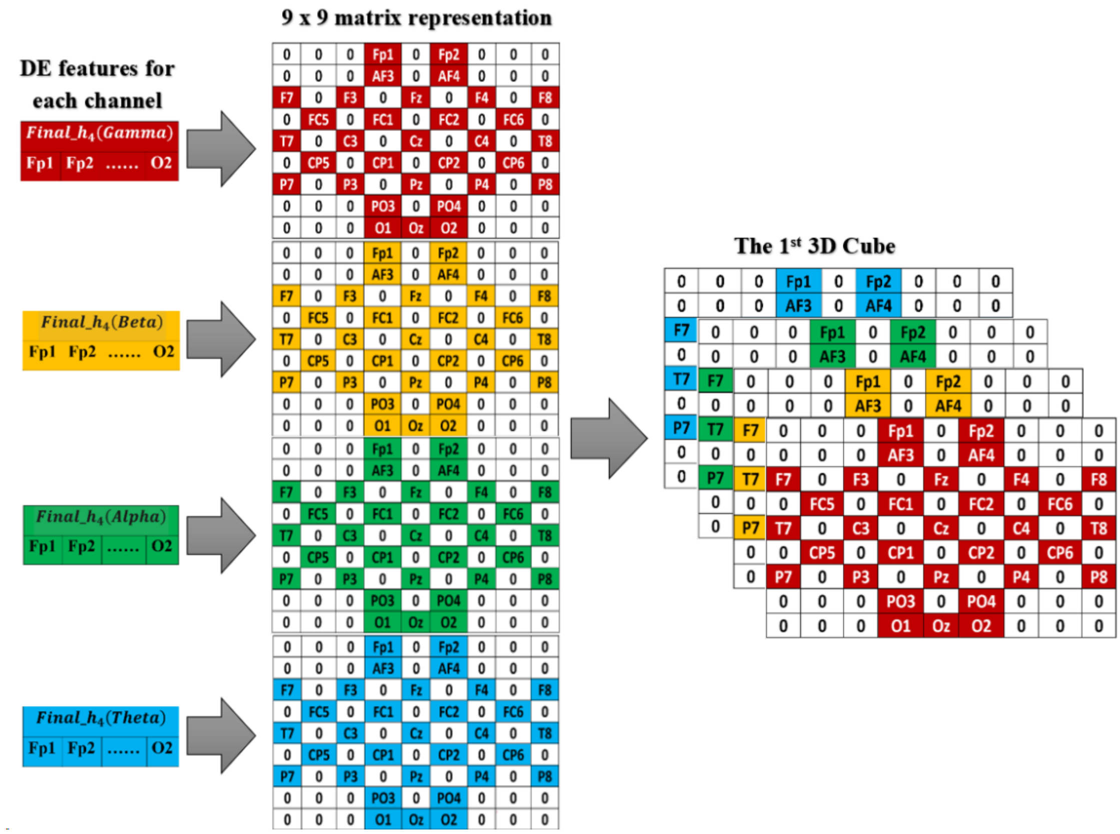

Figure 1. Illustration of feature representation on channels Fp1 to O2 for each frequency band using 3D cube

Gamma, beta, alpha, and theta frequencies are represented through a 9×9 matrix with red, yellow, green, and blue colors. The DEAP and DREAMER datasets produce 2,400 and 3,728 3D cubes for each participant. Furthermore, one participant generated 6,192 3D Cubes for long experiments on the AMIGOS dataset and 1,394 3D cubes for short experiments.

2.8. Classification

These three smoothing approaches are applied in the CNN method, to assess the success of the baseline reduction approach [7], [8], [22]. Figure 3 presents the architecture of the CNN method used to recognize four classes of emotions, namely high arousal positive valence (HAPV), high arousal negative valence (HANV), low arousal positive valence (LAPV), and low arousal negative valence (LANV). The CNN architecture in Figure 3 uses input data from data represented in a 3D cube. This data is then convolved four times to produce four feature maps. The first feature map measures 9×9×64, the second feature map measures 9×9×128, the third feature map measures 9×9×256, and the fourth feature map measures 9×9×64. The values in the fourth feature map are reshaped via the flattening process, resulting in a scalar value of 5,184 (9×9×64). This scalar value is used as input data at the input layer node. Next, this value is fully connected to the hidden layer with 1,024 nodes. Finally, the hidden node is fully connected to the output layer. In Figure 3, the output layer is four nodes. These four nodes represent the four recognized classes of emotions. Apart from the four emotion classes, this research will also recognize two emotion classes, high and low, for the emotion’s arousal and valence. The adam optimizer method updates the weight values, and L2 regularization calculates the error values. In addition, the learning rate, batch, and epoch parameter values are set at 0.0001, 128, and 50, respectively.

2.9. Assessment model and parameters

In this research, model evaluation uses k-fold cross-validation, where the k value is set at 10. Through k-fold cross-validation, the parameter evaluation process can be carried out. Some evaluation parameters are accuracy, error, precision, recall, and F1. Based on the precision and recall values resulting from the two emotion classes and the four emotion classes, the F1 value can be calculated.

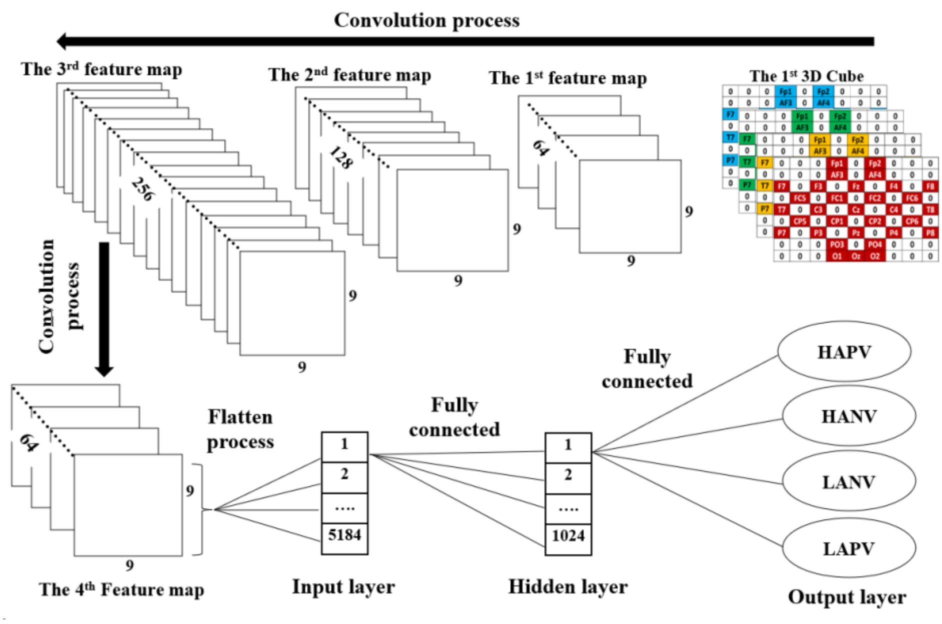

Figure 2. CNN architecture

3. RESULTS AND DISCUSSION

This study will employ three datasets, DEAP, DREAMER, and AMIGOS, to assess the dependability of the baseline reduction procedure on various data features. Table 10 shows the accuracy value of emotion recognition in the three DEAP, DREAMER, and AMIGOS datasets. According to the results of the tests, the Gaussian approach delivers good accuracy only in the DREAMER dataset for the two and four emotion classes. On the other hand, the mean filter approach can generate excellent accuracy for categorizing two and four emotion classes in the DEAP and AMIGOS datasets. The signal amplitudes of the three datasets will be compared to determine the source of this difference.

Table 10. The outcomes of three smoothing methods tests on three datasets

No	Smoothing	Emotion class	DEAP	DREAMER	AMIGOS
1	Default	Four class	79.83	81.01	94.06
2	Gaussian	Four class	72.77	92.88	93.72
3	Mean	Four class	95.48	79.79	97.61
4	Savitzky Golay	Four class	79.22	81.82	94.48
5	Default	Arousal	92.70	92.53	94.06
6	Gaussian	Arousal	91.69	96.94	92.84
7	Mean	Arousal	98.58	92.06	94.53
8	Savitzky Golay	Arousal	93.14	92.60	94.05
9	Default	Valence	91.73	89.96	96.70
10	Gaussian	Valence	90.48	96.05	96.10
11	Mean	Valence	98.07	88.90	97.30
12	Savitzky Golay	Valence	92.83	90.23	96.40

Figure 4 depicts the baseline signal pattern for the eighth participant in the eighth experiment before and after the smoothing operation. Figure 5 depicts the baseline signal pattern for the first participant in the first experiment before and after the smoothing technique. Figure 6 depicts the 1-second raw baseline signal from the DREAMER dataset for the tenth individual in the tenth experiment. The amplitude of the EEG signal should ideally be in the 100 μV range [23], [24]. Nonetheless, when capturing the baseline signal, different artifacts can intervene to raise the signal amplitude. Based on a comparison of the baseline signal patterns in the three datasets (Figures 4 to 6), it was discovered that the amplitude of the baseline signal in the DREAMER dataset is greater than the amplitude of the baseline signal in the DEAP and AMIGOS datasets. As a result, using the Gaussian filter method can reduce the amplitude of the EEG signal to an ideal value while producing more accuracy than using the mean filter approach. The Gaussian filter approach, on the other hand, alters the EEG signal pattern.

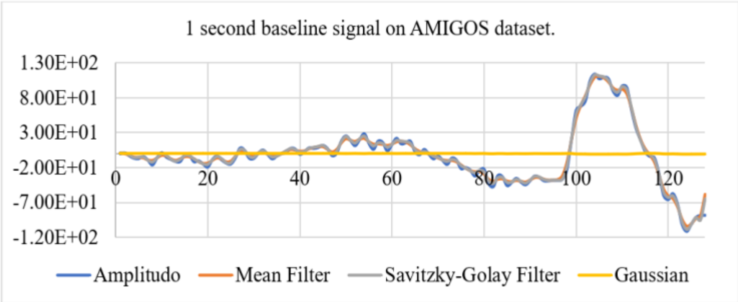

Figure 3. AMIGOS channel AF3 raw EEG signal data

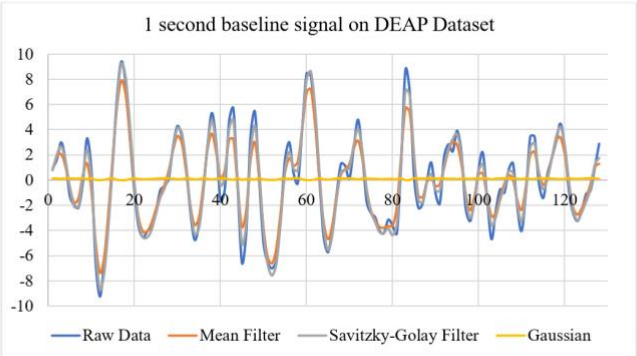

Figure 4. DEAP channel Fp1 raw EEG signal data

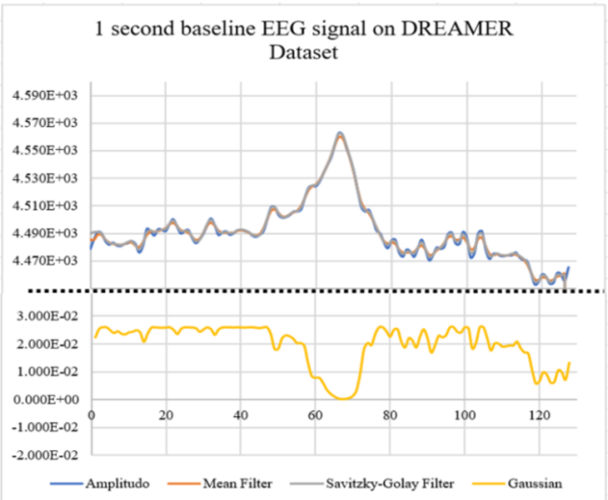

Figure 5. DREAMER's raw EEG signal data for channel AF3

The baseline reduction strategy has been used in many studies. However, the baseline signal employed in this study still contains artifacts. This phenomenon prevents the baseline reduction from performing optimally. Some researchers attempt to improve accuracy by applying a deep learning approach to the classification process, such as CNN [7], capsule network [22] combination CNN + long short term memory (LSTM) [25], and deep forest [3], but this classification method is not yet capable of recognizing the EEG signal pattern that is formed. The baseline signal smoothing procedure can improve the baseline reduction approach. The improved baseline reduction methodology can provide EEG signal patterns easily recognized by classification systems. Although this study and researchers [8] used DE, relative difference, 3D cube, and CNN methods for each process, the baseline signal that had been smoothed using the mean filter method was proven to be able to improve the performance of the baseline reduction process. These results are proven by increased recognition accuracy values for two and four emotion classes in the DEAP and AMIGOS datasets. The mean filter method proposed in this study can reduce baseline signals contaminated with artifacts compared to the other two smoothing methods. Although the mean filter approach can reduce the amplitude of the baseline signal and improve accuracy, it can only be used on EEG signals with an amplitude of 200 µV. Meanwhile, EEG signals can only be used in a Gaussian filter approach for signal amplitudes greater than 4,000 µV. These results are proven by increased recognition accuracy values for the DREAMER dataset's two and four emotion classes. This proposed method can reduce artifacts in the baseline signal without changing the existing EEG signal pattern. This research comprehensively reduced artifacts in the baseline signal using the mean filter and Gaussian methods. However, in-depth studies may be needed to determine the best method for reducing artifacts in the three datasets. In addition, further studies are essential to improve the classification process by determining appropriate classification methods. Using the CNN method in this research can result in the loss of spatial information from the EEG signal [21], [22], [26].

4. CONCLUSION

Our findings provide conclusive evidence that the smoothing procedure using the mean filter and Gaussian filter approaches are proven to eliminate artifacts in the baseline signal. These two approaches can increase baseline reduction performance by smoothing the baseline signal. The relative difference approach was employed in this study's baseline reduction process to generate EEG signal patterns that are easy to recognize throughout the classification phase, which impacts increasing accuracy. The CNN method for classification achieves the best accuracy value by introducing two classes and four classes of emotions. However, in-depth studies may be needed to determine the best method for reducing artifacts in the three datasets. In addition, further studies are essential to improve the classification process by determining appropriate classification methods. Using the CNN method in this research can result in the loss of spatial information from the EEG signal.

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