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Denoising of EEG signal based on word imagination using ICA for artifact and noise removal on unspoken speech

Efy Yosrita, Rosida Nur Aziza, Rahma Farah Ningrum, Givary Muhammad
Department of Informatics, Sekolah Tinggi Teknik PLN, Jakarta, Indonesia

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ABSTRACT

The purpose of this research is to observe the effectiveness of independent component analysis (ICA) method for denoising raw EEG signals based on word imagination, which will be used for word classification on unspoken speech. The electroencephalogram (EEG) signals are signals that represent the electrical activities of the human brain when someone is doing activities, such as sleeping, thinking or other physical activities. EEG data based on the word imagination used for the research is accompanied by artifacts, that come from muscle movements, heartbeat, eye blink, voltage and so on. In previous studies, the ICA method has been widely used and effective for relieving physiological artifacts. Artifact to signal ratio (ASR) is used to measure the effectiveness of ICA in this study. If the ratio is getting larger, the ICA method is considered effective for clearing noise and artifacts from the EEG data. Based on the experiment, the obtained ASR values from 11 subjects on 14 electrodes amounted are within the range of 0,910 to 1,080. Thus, it can be concluded that ICA is effective for removing artifacts from EEG signals based on word imagination.

Corresponding Author:

Rosida Nur Aziza
Faculty of Telematics for Energy
Institut Teknologi PLN
Jl.Lingkar luar barat, Jakarta Barat
Email: rosida@itpln.ac.id

1. INTRODUCTION

Electroencephalogram (EEG) is a reperesentation of the brain's electrical activity recorded via electrodes placed on the scalp [1-4]. It can be seen as the direct imaging visualization of electrical or magnetic signals produced due to direct brain nerve activity [5, 6]. The recording method is called Electroencephalograpy [7-10]. EEG is a key material for developing a brain computer interface (BCI) communication system [11], which helps people communicate with their environment [12-14], especially for people who have problems with body motor function [15-17], brain injuries such as stroke [18], lock in syndrome [19]. Lotte (2018) defines BCI as a system that translates the patterns of a user brain activity into messages or commands for interactive applications [20]. EEG signals are generated from complex working system, so they are susceptible to be interfered with signals originating from other sources called artifacts, such as muscle movements, eye movements, heart rate and electrical signals. In general, the artifacts are divided into non-biological artifacts, suh as the placement of electrodes and electrical voltages, and biological artifacts including eye flashes, eye movements, muscle movements and heart rate [8]. To clean the signal from the artifacts, there are various methods such as ICA, PCA, discrete wavelet transform, stationary wavelet transform, and the morphological component analysis (MCA). Among the methods mentioned previously, the most widely used method for removing artifacts from EEG signals is ICA. The reason is because it is very effective for denoising muscle movement artifacts [21], eye blink, and recognized to produce optimal results with a wide range of scenarios [2]. However, there is still a need for visual inspection of the separate independent components [8].

Here are some of the studies using ICA methods for denoising artifacts, including a research by Sheela (2020), that combines independent component analysis (ICA) and transient artifact reduction algorithm (TARA) to remove the ocular (flicker and eye movement) artifacts [1] and Kim (2013), who has implemented ICA to remove EOG [22]. The combination of independent component analysis (ICA) and canonical correlation analysis (CCA) method with discrete wavelet transform and stationary wavelet transform to remove the movement artifacts is also examined [7]. Other studies have proposed automatically removal of artifacts with generic ICA-based algorithms and unsupervised [2], a new ICA-based finger print method to automatically remove physiological artifacts [8], a systematic way to remove artifacts using the morphological (MCA) [23]. Jiang (2019) has conducted a review study on methods for denoising the artifacts and states that ICA is the most commonly used method [10].

The calculation of the artifact to signal ratio (ASR) is performed to investigate the effectiveness of ICA [24] because the EEG data obtained from experiments is unknown the ground truth, so that the author did not calculate ASR as in some previous studies [25, 26] . In this study, the authors examine the effectiveness of ICA methods to remove artifacts from raw EEG signals based on word imagination, acquired from the experiment, which was conducted in basic computer and computer network laboratories of IT PLN. The number of the subjects participated in this experiment was 11 (eleven) people, consisted of 4 female and 7 male IT-PLN students who ranged from 18 to 23 years old.

2. RESEARCH METHOD

The following are the stages of the experiment, as described in Figure 1:

a) The phase of acquisition of EEG Sinyal with four different scenarios, i.e. looking at the images that descibe an activity or a thing related to the words: eat, drink, hungry, thirst, happy, sad, sick and toilet, using EPOC Emotiv + and emotivPro for recording the EEG signals.
b) The Raw EEG data obtained is then cleaned from artifacts/noises using ICA method, by segmenting data per 2 seconds followed by the decomposition based on frequency. The selected frequency ranges are between 4-8 Hz known as theta wave, 8-12 Hz known as alpha wave and 12-30 Hz known as beta wave.
c) To measure the effectiveness of the process of artifacts removal by measuring artifact to signal ratio (ASR)

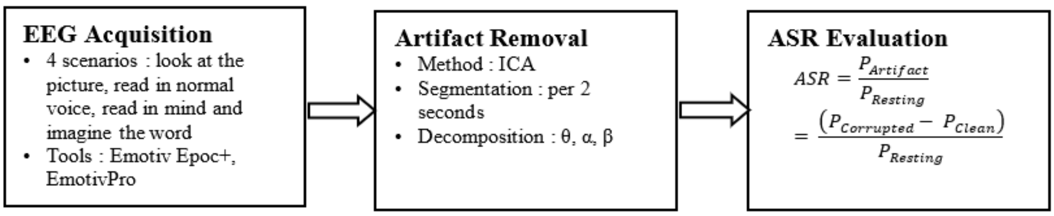


Figure 1. The Stages of the Experiment

The EEG data was retrieved from 11 (eleven) research participants, consisted of 7 male and 4 female students with the range of age between 18-23 years old. They are the student of Informatics Department of IT-PLN. These are the stages for data acquisition process, as shown in Figure 2:

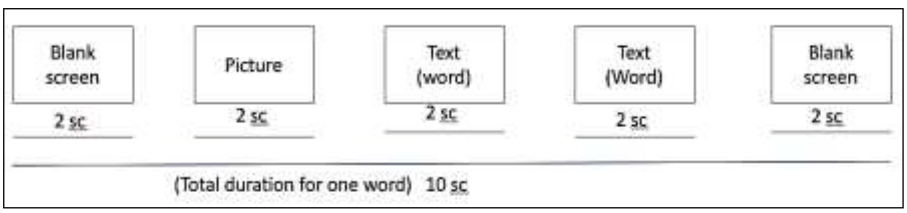


Figure 2. Procedure for the Data Acquisition

a) Subjects were requested to sit casually and not to do any movement.
b) They were requested to look at slides showing images that visualized activities representing 8 (eight) words: “MAKAN” (eat), “MINUM” (drink), “LAPAR” (hungry), “HAUS” (haus), “SENANG” (happy), “SEDIH” (sad), “SAKIT” (sick) and “TOILET” (toilet) with the time duration for each word was 2 seconds.
c) After completion of stage (2), the subjects were asked to read the texts that displayed the words “MAKAN” (eat), “MINUM” (drink), “LAPAR” (hungry), “HAUS” (thirsty), “SENANG” (happy), “SEDIH” (sad), “SAKIT” (sick) and “TOILET” (toilet) with normal voice. The length of time for each word was 2 seconds.
d) After completion of stage (3), the subjects were asked to read silently the texts that displayed the words “MAKAN”, “MINUM”, “LAPAR”, “HAUS”, “SENANG”, “SEDIH”, “SAKIT” and “TOILET” and the duration of time for each word was 2 seconds.
e) After completion of stage (4), the subjects closed their eyes and imagined the words “MAKAN”, “MINUM”, “LAPAR”, “HAUS”, “SENANG”, “SEDIH”, “SAKIT” and “TOILET”. The duration of time for each word was 2 seconds.
f) Activities 2 to 5 were repeated 5 times for each research subject.

In order to remove the artifacts that come from eye blinks, muscle movements, heartbeat, electrical voltages, and other possible artifacts from EEG data using ICA method, there are several steps that shoud be performed. Figure 3 below depicts the stages for the artifact removal process .

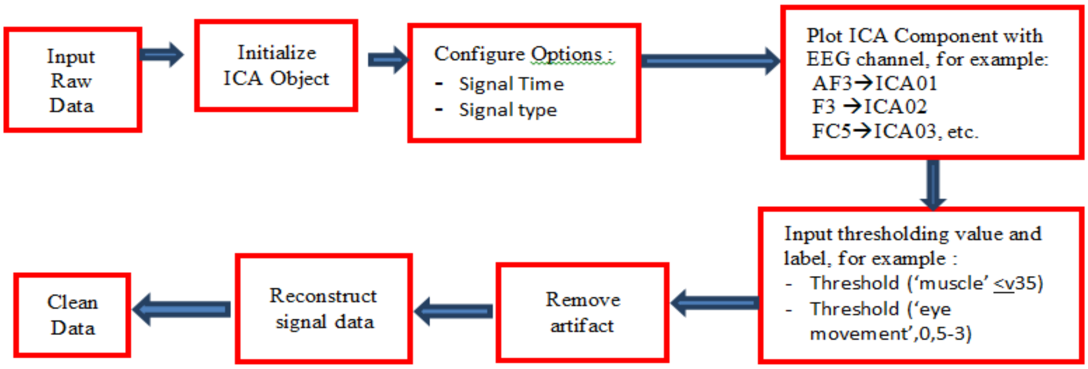


Figure 3. Artifact removal process

The process begins with inputting the EEG raw data, and then followed by the initiation of ICA objects and the configuration of time and type of signal. The next stage is to apply bandpass filtering with default setting, for low frequencies at 1 Hz and high frequency of 100 Hz. Each electrode is named/coded, electrode AF3 is named ICA01, F7: ICA02, F3: ICA03, FC5: ICA04, T7: ICA05, P7: ICA06, O1: ICA07, O2: ICA08, P8: ICA09, T8: ICA10, FC6: ICA11, F4: ICA12, F8: ICA13, and AF4 is coded as ICA14. After the plotting, the threshold values are defined for removing artifacts from certain sources, for example: the threshold value for the heart beat is > 1 Hz, for muscle is < 35Hz. The artifact removal is executed, followed by the reconstruction data to obtain the clean EEG signal. Here is the threshold value setting process implemented in the code for the artifact removal:

```
# Load raw data
# Defines the bandpass
# Set ICA components = 14
# Configure signal type= EEG
# Configure signal time = 2 sc
# Compute ICA start = 0 and stop = 256
# Custom thresholding value
 # Define the heart threshold (> 1Hz)
# Define the muscle threshold (<= 35Hz)
# Define the eye threshold (0.5 - 3Hz)
# Define the transmission_line threshold (50 - 60Hz)
```

The calculation of artifact to signal ratio (ASR) is performed to examine the effectivity of ICA for denoising EEG signal [24]. The following the formula of ASR.

$$ASR = \frac{P_{Artifact}}{P_{Resting}} = \frac{(P_{Corrupted} - P_{Clean})}{P_{Resting}} \tag{1}$$

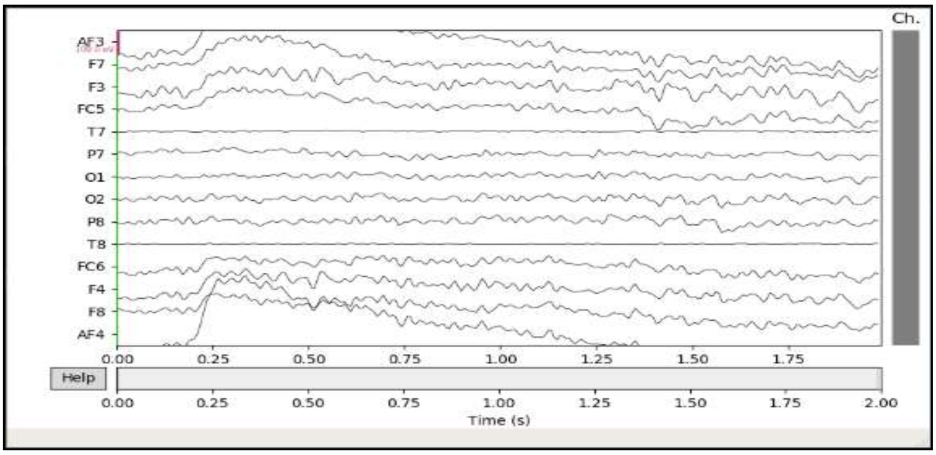
Where :

$P_{Corrupted}$ = signal obtained when subject is doing a certain activity
$P_{Resting}$ = signal obtained when subject is in resting condition
P_{Clean} = signal that has been denoised

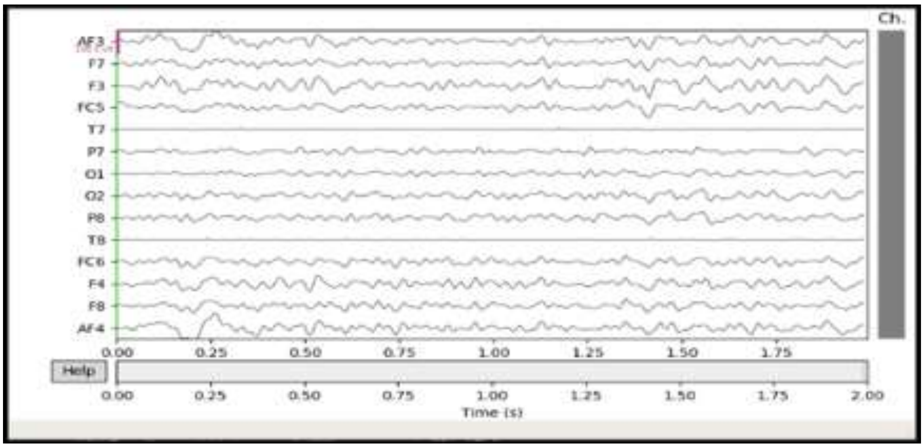
3. RESULTS

The obtained raw data from Emotiv Epoc+ and EmotivPro is presented in 3 forms, i.e.: signal representation in graphic, EDF and CSV files. Figure 4 shows the example of the EEG signal representation obtained when a test subject was performing the task to imagine the word “makan”. Figure 4(a) shows one of the raw EEG signals dan Figure 4(b) shows the clean EEG signal from 14 electrodes, AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. The figures are obtained when a subject was imagining the word “makan” and its duration was 2 seconds. X axis represents times and Y axis describes the names of the electrodes.

From Figure 4(a), it can be observed that there are some artifacts that appeared in several electrodes during the data acquisition period. After the denoising process using ICA, the resulting signals from each electrodes look more stable and smooth as shown in Figure 4(b).



(a)



(b)

Figure 4(a)-(b). Raw EEG signal dan Clean EEG Signal obtained when imagining the word “makan”

To calculate the ASR, the writer uses data in the EDF format. For the data sampling, the authors use 10 sampling points when the test subject is in the resting condition and 10 sampling points when the subject looks at the image associated with the word "makan" from all Emotiv Epoc+ electrodes (14 electrodes). For each electrodes, the means of the voltage amplitudes of the resting period, raw data, and clean data are calculated. Based on the calculation, the resulting value of the ASR are in the range of 0.910 to 1,080. Referring to the previous research conducted by Bono (2018) [24], the obtained ASR value far from 0 (zero) indicates better performance. The following is one example of an ASR value chart from subjects 3, as shown in Figure 5. Figure 5 describes the ASR values of one test subject (S6) taken from 14 electrodes. The graph shows that the influence of ICA for each electrode is different within the range 0.910 to 1.001 of ASR values. With the highest value of ASR is from the F7 electrode (0.910) and the lowest value is from the F4 electrode (1.001). Figure 6, displays the ASR values of 11 subjects on 1 electrode (AF4). Shows that the influence of ICA on the eleven different subjects produced almost the same ASR value, which is in the range of 0.910 to 1.080.

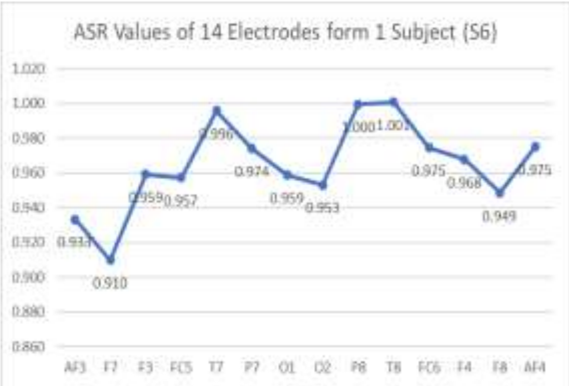


Figure 5. ASR Values of 14 Elektroda from S6

Figure 6. ASR Values on 1 Electrode (AF4) from 11 Subject

4. CONCLUSION

EEG signals are generated from the activities of the human brain. They are contaminated by some unwanted signals, known as artifacts. Despite the fact that a number of artifact removal methods have been developed, the methods with high accuracy and efficiency are still need to be identified. ICA has been known for its ability to remove several kinds of artifacts. So, this method is implemented in this research to remove the artifacts from the EEG signals obtained when several test subjects were asked to look at and imagine certain words. The value of ASR is calculated to examine the effectiveness of ICA in removing artifacts. Based on the calculation, the resulting ASR values from different subjects are within the range of 0.910 to 1,080. This means that the difference between the EEG signals accompanied with artifacts and the clean EEG signals is significant. So, it can be concluded from the experiment that ICA is effective for eliminating the artifacts from EEG signals based on word imagination.

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