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Power Spectrum and Data Clustering Analysis for Intraoperative EEG Signals

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Authors' contributions

This work was carried out in collaboration between all authors. All authors designed the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript and managed literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Intraoperative EEG is used for acquiring brain signal that probes or electrodes placed on brain organ directly. It is different from common EEG, which probes placed on scalp. In order to explore the characteristic of brain signal based on brain injuries case, data taken from ten subjects while applied intraoperative EEG. The signals acquire by placing eight channels on brain organ simultaneously with particular form of probes.
For comparing the brain signal among the subjects, power spectrum chosen as basic method. The power spectrum indicates the energy of signals, representing the brain activity. Cross checking between powers spectrum and brain injuries case, data clustering applied using self-organizing maps.
Calculating the power spectrum of signals shows that brain stroke case has higher value than non-stroke case. This higher value exists for most of channels. Using channels as dimension of data, self-organizing maps visualize that stroke case's position are closed to each other on map. On map

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also, visualize the boundary between stroke and non-stroke case. Based on brain injuries happened among the subjects, stroke case has specific signals characteristic, which different from non-stroke significantly.

Keywords: Intraoperative electroencephalograph (EEG); power spectrum; fast fourier transform (FFT); data clustering; self-organizing maps (SOM).

1. INTRODUCTION

This paper constructed by some sections. Section 1 is about introducing, short description about intraoperative EEG and signal gotten that will be related to the brain injuries case. Section 2 is about subjects, EEG instrument used, and method applied. Section 3 is about result and analysis. Section 4 is about conclusion of this study.

Brain consists of by particular number of nerve cells and it is 100 billion cell approximately. Based on sodium and potassium movement along the nerve cell, there is potential difference exist. The rest potential in the nerve cell is about -70 millivolts. When nerve cell transmits the signals to the others nerve cell, cumulatively produce the brain signal that could be measured by particular instrument. Electroencephalograph (EEG) is an instrument for monitoring brain activity, especially brain signal [1]. EEG is measured the potential difference between reference point and others point which is to be measured. Reference point usually uses ear as reference, but there is others method for providing reference point. Particular number of others points said as EEG's channel. In acquiring the signals, EEG's channel uses probes or electrodes placed on scalp. Probe position can adopt the 10/20 systems, it is standard for probes placement [2]. There is typical brain signal based on EEG measured such as alpha rhythm, beta rhythm, delta rhythm, gamma rhythm, etc. These typical signals related to particular condition of the human.

There is another type of EEG that used for special purpose and little bit different. It is intraoperative EEG. The intraoperative EEG is used to monitor brain activity while do neurosurgery. Basically, intraoperative EEG is similar in measuring the potential difference but the mainly different that the probe has specific material and form, see Fig. 1. In intraoperative EEG, the probes or electrodes placed on brain organ directly [3], see Fig. 2. Considering the placement and probe contact that the probes has special material and form as mentioned before. Based on form and placement, there is no standard probes position. In addition to monitor the brain activity, advance usage of intraoperative EEG is detecting the new tissues on brain, such as tumor. Using database of signal characteristics, intraoperative EEG could recognize whether the tissue is brain or not. It is helpful to assist the neurosurgeon in removing not brain tissues. The signal characteristic in intraoperative EEG is different with typical signal EEG such as alpha rhythm for example.

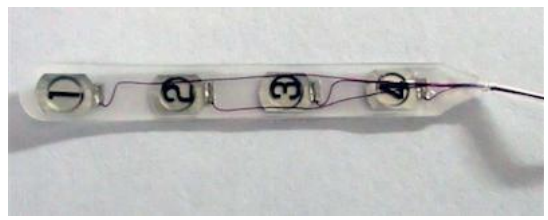

Fig. 1. Probes for Intraoperative EEG

In order to characterize the signals that coming from intraoperative EEG according to particular brain injuries, this study proposes power spectrum analysis [4] as basic method used. Power spectrum indicates the energy that belonging to the signals. This power spectrum base analysis is in order to make discriminant among to the brain injuries happened. To support signal characteristics, data clustering applied based on power spectrum value. The data clustering tried to group the object based on date given, in this case is power spectrum. Output of clustering will crosscheck with medical data.

The basic method used in calculating power spectrum is Fast Fourier Transform (FFT) algorithm. This algorithm transforms the signal from time domain into frequency domain [5,6]. Power spectrum value taken from signal, which is in particular frequency. The focus frequency chosen is 8-12 Hz. It is alpha rhythm bandwidth. Alpha bandwidth used because this range commonly used as indicator for human to response particular stimulation [7]. Band-pass filtering used for focusing the signal in particular range of frequency. Assigning the signal with zero value if the frequency outside of the range then calculates the power spectrum in rest of signal. Power spectrum value compare to each other's based on brain injuries cases. The comparison it tries to explore whether the power spectrum reflects the brain injury happened or not.

Beside comparison, the power spectrum value obtained before clustered. The clustering uses multi dimension data that each power spectrum from a channel treats as dimension. Self-Organizing Maps (SOM) used as data cluster algorithm [8]. This clustering method visualizes the multi dimension of data into two dimensions by calculating the distance in every dimension recursively. Data clustering applied to form group of data based on power spectrum value. The visualization of group then crosschecked to the medical data. The data cluster used whether the group formed reflecting the same of medical data or not.

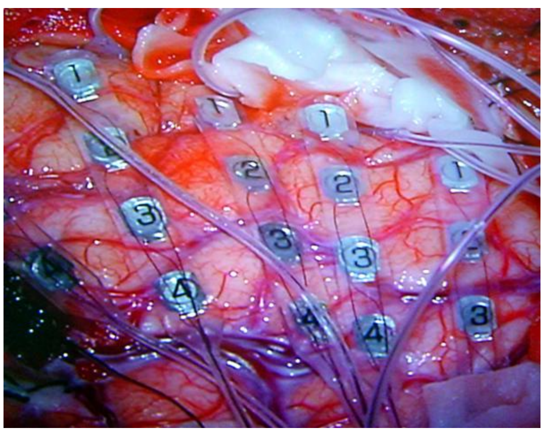

Fig. 2. Probes placement

Method and technique used in this study apply to data of intraoperative EEG signals. The intraoperative EEG signals are taken from nine subjects. The subjects have many different types of brain injury and others medical data. The signal acquired when the subjects in neurosurgery for particular medical treatments. The EEG instruments has eight channels and 250 Hz sampling rate. The channels grouped into two probes, see Fig. 1. On power spectrum calculation among the channels, shows that brain stroke case has power spectrum value larger than the other brain injuries cases. Also in visualization of data clustering, brain stroke case has near distance relatively. Based on comparison of power spectrum value and data cluster visualization, the signal taken from intraoperative EEG reflects some of brain injury case relatively.

2. REVIEW OF INTRAOPERATIVE EEG

There were many experiments that utilize EEG as instrument for intraoperative monitoring while brain surgery.

Levy [9], used intraoperative EEG to compare between the patients undergoing anasthetic inductions and the patients undergoing cardiopulmonary bypass. Levy found that there is the signal characteristic belong to the patient condition showed by two peak averaged 7.6 Hz. The Levy experiment was little bit different with the author, but it still used as reference because the intraoperative EEG able to characterize for many patient conditions.

Murashita et al. [10] utilized intraoperative EEG in aortic arch surgery. Result obtained by Murashita that intraoperative EEG is reliable monitoring tool for safe circulatory arrest. This result based on intraoperative EEG with abnormal pattern. This experiment different with author experiment but the conclusion that intraoperative EEG is reliable tool that very attracted for author's experiment.

Based on review of intraoperative EEG method, especially the result which obtained from experiment, the intraoperative EEG could be proper tool to characterize of particular brain injuries by exploring the signal output from the instrument.

3. DATA AND PROCESS

This section describes about the subject information especially the brain injury happened, the instrument used for signal acquisition and method applied for analyzing the signals.

3.1 Patients and Acquisition

Eligible patients were aged 18 years and over and admitted to the Department of Neurosurgery, Faculty of Medicine, Universitas Padjadjaran – Dr. Hasan Sadikin General Hospital, Bandung, Indonesia from 19 June 2015 to 19 June 2016.

Ethical approval was obtained from the Faculty of Medicine, Universitas Padjadjaran Ethics Committee (No.413/UN6.C1.3.2/KEPK/PN/2015). During a period from November 2015 until March 2016 there were 10 patients that underwent craniotomy for treatment of their respective diseases. All of the surgical procedures were carried out at Dr. Hasan Sadikin General Hospital Bandung. Patient must be an adult and agreed the informed consent to be included in this study.

3.2 Data

There were ten subjects with various type of brain injury. Particular medical treatment did by doing neurosurgery. Intraoperative EEG signals obtained on this neurosurgery. Details data about the subject can be seen on Table 1. Beside the data as basic information of the patients, it will be used for clustering the patient also.

3.3 Instrument

In acquiring the brain signal during neurosurgery, particular probes or electrodes and acquisition unit used. On probe, four channels grouped into a piece of probe. So, total eight channels grouped into two pieces of probe. These channels using monopolar which measure the potential difference with reference directly. In acquisition process there were no configuration to adjust in getting particular signal because the signal analysis did after acquisition. This particular form of probes considering for placement on the brain organ directly, see Fig.1.

For reference point, it uses reusable gold-plated probe. The reference probe was placed on ear. In acquisition unit, the sampling rate was set at 250 Hz. The acquisition unit uses ADS1299EEG-FE as main Analog Digital Conversion (ADC) engine released by Texas Instruments. This ADC designed for EEG specifically.

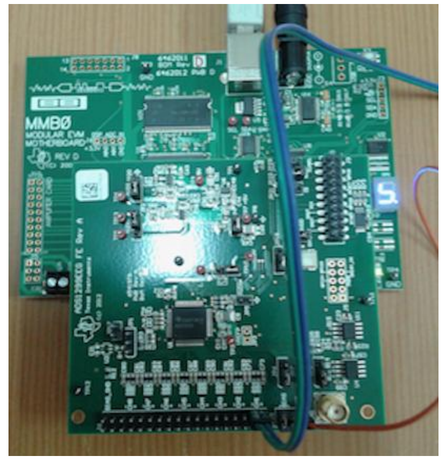

Fig. 3. Acquisition unit

3.4 Power Spectrum

To calculate the spectrum from particular frequency, the signal transformed from time domain into frequency domain initially. Fast Fourier Transform (FFT) algorithm used in this study for transforming the intraoperative EEG signals.

$$X(\omega) = \int_{-\infty}^{\infty} x(t)\, e^{-i\omega t} dt \qquad (1)$$

Following (1), the intraoperative EEG signal, $x(t)$, there were particular value x based on time t. As mentioned before, the instrument set at 250 Hz sampling rate. So there were 250 particular values where t in one second. See Fig. 4, the example of intraoperative EEG signal in one minute. Based on FFT algorithm, $x(t)$ construts periodic signal of $\tilde{x}(t)$ with T period. Spectrum $\tilde{x}(t)$ is sampling output of $x(t)$.

Table 1. Subject medical data

Subj[a] no.	Sex[b]	Age[c]	Injury	GCS[d]	Time[e]
1	M	57	Epidural hematoma	14	11
2	M	60	Epidural hematoma	9	5
3	M	17	Epidural hematoma	12	19
4	F	29	Skull defect	14	2160
5	F	19	Epidural hematoma	15	5
6	F	50	Brain stroke	13	12
7	M	20	Epidural hematoma	15	6
8	M	28	Epidural hematoma	13	15
9	M	53	Brain stroke	15	2160
10	M	58	Tumor	15	1440

[a]Subject, [b]Sex: M as Male and F as Female, [c]Age in years, [d]Glasgow coma scale, [e]Delay before medical treatment in hour

On this study, range of frequency will be used is alpha band-with, 8-12 Hz. So, spectrum calculation focus on periodic signal, $\tilde{x}(t)$, with T period that produce frequncy in range 8-12 Hz. See Fig. 5, the example of intraoperative EEG signal in frequency domain and in range of 8-12 Hz.

$$c_k = \frac{1}{T} X(kw_0) \quad (2)$$

Following (2), spectrum c_k from periodic signal $\tilde{x}(t)$, is obtained by sampling from $x(t)$ in point of kw_0 with $\frac{1}{T}$ scale. Power spectral density is power of two the c_k.

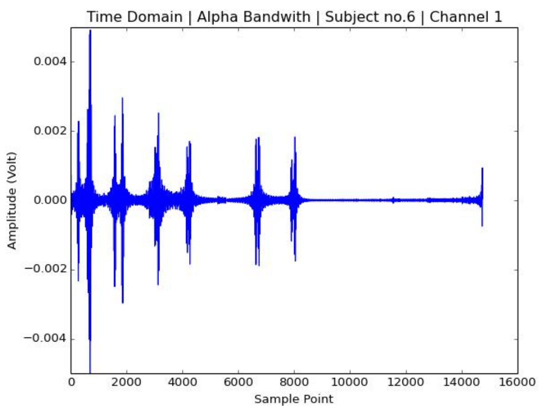

Fig. 4. Intraoperative EEG signal of subject no. 6 on channel 1

The FFT algorithm apply to the intraoperative EEG signals from eight channels in a subject. From FFT algorithm implementation, power spectral density obtained for analyzing the signals to each other.

3.5 Data Clustering

Power spectral density value obtained before in each channel clustered among the all subjects. This clustering taken to visualize the cluster of subject based on power spectral density owned. Group of data obtained then crosscheck with medical data owned by the subject. The purpose of this data clustering try to analyze whether the power spectral density represent some of medical data among the subject. Data clustering use Self Organizing Maps (SOM) algorithm. SOM algorithm maps multi-dimensional data into two-dimensional data.

$$W_v(1+t) = W_v(t) + \theta(u,v,t).\alpha(t).\big(D(t) - Wvt \quad (3)$$

Following (3), the updated version node v in step t with vector weight W_v obtained by adding the previous weight W_v with combination among neighborhood function, learning rate, and the distance. Neighborhood function, $\theta(u,v,t)$ gives the distance node between node v and node u, which u is the index of Best Matching Unit (BMU) of $D(t)$; $D(t)$ is input vector. The learning rate α, will decrease with step t.

In a subject there were eight power spectral density where subject became node with power spectral as vector. Submit the node into SOM algorithm, equip with 40 by 40 shape and 10.000 times iteration. This iteration number ensure that the all node homogenous finally. SOM implementation using tools that provided by Multivariate Pattern Analysis in Python [13].

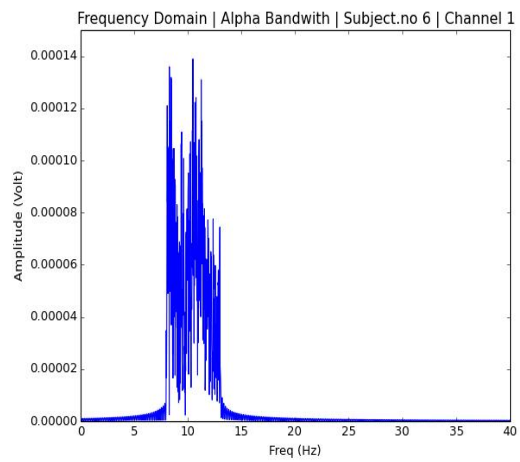

Fig. 5. Intraoperative EEG Signal in frequency domain of subject no.6 on channel 1

4. RESULTS

4.1 Power Spectral Density

Applying (1) on the raw of intraoperative EEG signals obtains the signal in frequency domain. Thus, selected spectrum on range of frequency 8-12 Hz apply power of two. Power Spectral Density is summary of these power of two. The value of power spectral density for each channel on all subjects can be seen on Table 2. On the last column of Table 2 is average of power spectral density among the eight channels.

Table 2 shows that subject no.6 and no.9 has average power spectral density larger than others, especially subject no.6. If all average power spectral density sorted by the highest into the lowest value, subject no.6 and no.9 are in the top two rank. Crosschecked with the subject medical data on Table 1, subject no.6 and no.9 has similar brain injury and closed age. The brain injury is brain stroke. Subject's age didn't effected to power spectral density since even the subject younger or older from subject no.6 and no.9, the power spectral density still below from no.6 and no.9.

4.2 Data Clustering Visualization

In visualizing of the clustered data, Self-Organizing Map (SOM) algorithm used. To implement SOM algorithm in power spectrum density data, python programming language as tool [11-13]. Here is the some code of used:

```
vector = min_max_scaler.fit_transform(vector)

som = SimpleSOMMapper((40, 40), 10000,
      learning_rate=0.05)

som.train(vector)
```

Power spectral density obtained for each channel in subject treat as initial dimension of data. So for each subject has 8 dimension of data and said as *vector* in code. Before the data enter into train process, it should be normalized first. In shape 40x40, 10.000 iterations did in order to visualize group of data based on dimensions owned. The result of this data clustering technique can be seen on Fig. 6.

On Fig. 6 shows that subject no.6 and no.9 are closed. The visualization is match with the data on table II that subject no.6 and no.9 has average power spectral density larger than others, especially subject no. 6. Crosscheck with medical data on table I thatno.6 and no.9 has similar brain injury, it is brain stroke. It could be said that brain stroke injury has larger power spectral density than other particular type injury.

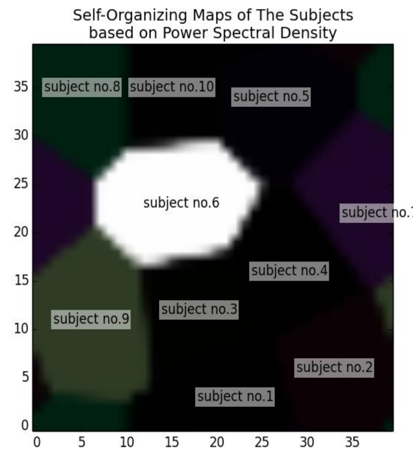

Fig. 6. Subjects clustering based on power spectral density

4.3 Medical Data Clustering

In previous section, data clustering applied in power spectral density that each channel become dimension of data. This section tried to cluster the subject based on the medical data. The medical data used as dimension were gender, age, brain injury, GCS, and time delay, which age and brain injury transform first into interval scale measurement.

Table 2. Total power spectral density (10^{-6} volt^{2}) on range 8-12 HZ for 1 minute of data acquisition

Subj. no.	Channel								Average
	1	2	3	4	5	6	7	8	
1	0.005	0.006	0.292	0.028	0.006	0.059	0.051	0.063	0.064
2	21.116	13.690	36.294	3.784	6.955	9.426	15.191	22.135	16.074
3	1.915	2.872	2.972	3.697	3.122	3.251	2.814	2.196	2.855
4	1.592	3.441	1.590	1.589	1.587	1.590	-	1.592	1.623
5	15.883	0.091	0.091	0.086	0.091	9.807	4.761	35.115	8.241
6	363.718	516.295	592.241	439.783	645.703	641.857	1,831.963	564.536	699.512
7	5.930	1.425	191.095	5.734	35.711	3.198	350.288	68.061	82.680
8	0.042	0.065	0.193	1.012	243.693	0.033	247.045	2.436	61.815
9	157.168	33.670	34.111	116.363	161.714	129.578	131.599	126.520	111.340
10	0.168	0.158	0.210	9.677	0.273	0.214	0.207	0.182	1.386

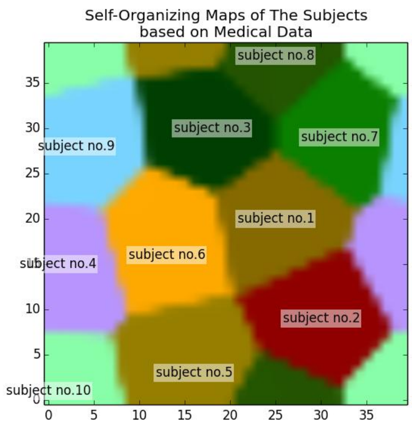

Fig. 7. Subjects Clustering based on Medical Data

On Fig. 7, can be seen that subject no.6 and no.9 has closed distance based on dimension given. Analyzing the visualization output of data cluster based on power spectral density and based on medical data, subject no.6 and no.9 has closed distance consistently. Subject no.4 has closed distance with no.9 because there was similar time delay before medical treatment that larger than the others extremely.

5. CONCLUSION

Intraoperative EEG is method for monitoring the brain activity by measuring potential difference between points at brain organ and other point as reference. Applying some algorithm for justification of signal features and crosschecked with medical data, the conclusion for this study are:

1. Analyzing the power spectral density among the subjects that brain stroke injury has larger value than others particular injuries. This analyzing crosschecked with data clustering that brain stroke injury has closed distance in visualization.
2. Power spectral density reflects the brain injury case especially the brain stroke case.
3. Comparison the visualization of data clustering between power spectral density based and medical data based that subject no.6 and no.9 were closed consistently.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Millett D. Hans Berger: From psychic energy to the EEG. Perspect Biol Med. 2001;44(4):522-42.
2. James Rowan A, Eugene Tolunsky. A primer of EEG: With a Mini-atlas. Publisher: Butterworth-Heinemann; 2003.
3. Mahmud M, Girardi S, Maschietto M, Bertoldo A, Vassanelli S. Processing of neuronal signals recorded by brain-chip interface from surface of the S1 brain cortex. Proceedings of the 2010 IEEE 36th Annual Northeast Bioengineering Conference; 2010.
4. Ian Kaplan. Spectral analysis and filtering with the wavelet transform. Augustus; 2002. Available:http://www.bearcave.com/misl/misl_tech/wavelets/freq/
5. Meenakshi, Singh RK, Singh AK. Frequency Analysis of Healthy and Epileptic Seizure in EEG using Fast Fourier Transform. International Journal of Engineering Research and General Science Volume. 2014;2(4):683-691.
6. John G Proakis, Dimitris G Manolakis. Digital Signal Processing Principles, Algorithms and Applications. Publisher: Prentice-Hall of India Pvt Ltd; 2000.
7. Teplan M. Fundamentals of EEG measurement. Measurement Sci. Review. 2002;2(2).
8. Kuzmanovski I, Trpkovska M, Soptrajanov B. Optimization of supervised self-organizing maps with genetic algorithms for classification of urinary calculi. Journal of Molecular Structure. 2005;744:833-838.
9. Levy WJ. Intraoperative EEG patterns: Implications for EEG monitoring. Anesthesiology. 1984;60(5):430-4.
10. Murashita T, Pochettino A. Intraoperative electroencephalogram-guided deep hypothermia plus antegrade and/or retrograde cerebral perfusion during aortic arch surgery. Journal of Cardiac Surgery. 2016;31(4):216-219.

11. Python Software Foundation; 2001. Available:https://www. python.org/
12. Pedregosa F, Varoquaux G, Gramfort A, et al. Scikit-learn: Machine Learning in Python. The Journal of Machine Learning Research. 2011;12:2825-2830.
13. Hanke M, Halchenko YO, Sederberg PB, Hanson SJ, Haxby JV, Pollmann S. PyMVPA: A python toolbox for multivariate pattern analysis of fMRI data. Neuroinformatics. 2009;7(1):37-53.

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