epilepsi deteksi

by Ade Efiyanti

Journal of Physics: Conference Series

PAPER • OPEN ACCESS

Epilepsi detection system based on EEG record using neural network backpropagation method

To cite this article: Ade Eviyanti *et al* 2019 *J. Phys.: Conf. Ser.* **1381** 012037

Epilepsi detection system based on EEG record using neural network backpropagation method

Ade Eviyanti1, Hindarto hindarto[2], Sumarno[3], Herlian Aliyasa Alamj Duddin[4]

Program Studi Informatika, Universitas Muhammadiyah Sidoarjo, Jl. Raya Gelam 250 Candi Sidoarjo

adeeviyanti@umsida.ac.id[1], hindarto@umsida.ac.id[2], sumarno@umsida.ac.id[3], aliyasa@umsida.ac.id[4]

Abstract. Epilepsy is a manifestation of brain disorders with a variety of etiologies, but with the typical single symptom, periodic and reversible attacks, Epilepsy is characterized by an excess amount of electricity coming out of the brain cells, which can cause seizures and abnormal movements. EEG signals on epilepsy attacks have a characteristic pattern that allows health professionals to distinguish them from normal conditions (nonseizure). There are many methods used by researchers to recognize patterns of EEG epilepsy and non epilepsy signals in this study using Discrete Cosinus Transform (DCT) to perform the extraction of EEG signal features and Backpropagation Neural Networks for identification of EEG signal patterns. This research data using five classes of data sets of digital EEG signal taken from clinic Epileptologie University of Bonn ie data set A normal open eye signal, set B normal eye closed signal, C set enter the epilepsy zone, set D enter epilepsy, set E epilepsy seizures. The five class data are processed using DCT to obtain feature extraction, so results from DCT are used to perform identification using the Backpropagation method. The results of this study indicate that with feature extracted using DCT and identification process using Artificial Neural Network Backpropagation got EEG signal identification obtained for data set A, B, C, D and E is 76%, for set AB and CDE class data 73 %.

1. Introduction

Epilepsy is a chronic neurological disease caused by abnormal electrical activity in the brain. As we know that our brain consists of about one hundred billion nerve cells called neurons, where they carry signals throughout the brain and between the brain to other parts of the body. Each neuron generates an electrical signal which is then spread by the neuro transmitter in the form of a nerve-conducting signal [1].

Electroencephalography (EEG) is a method used in measuring spontaneous electrical activity from the brain that is obtained by firing electrical signals into neurons in the brain[2]. The EEG signal recording process is carried out in a short time, usually for 20-40 minutes. Records are obtained by placing electrodes in various positions on the scalp[3]. There are two approaches to get EEG signals, namely invasive and non-invasive approaches. A noninvasive approach can be applied repeatedly for patients, normal adults, and children with almost no risk or limitation, so that almost all adult EEG recordings are done non-invasively [2]. EEG signal data used in this study is in the form of time series.

Transforming an EEG signal into a model, is a very effective way of assisting in the classification of EEG signals, identifying and estimating the spectrum of EEG signals. EEG signals contain certain components, known as alpha (8-13 Hz), beta (14-30 Hz), theta (4-7 Hz), and delta (0.5-3 Hz), so the transformation of EEG signals into frequency regions are very useful, especially in the identification of waves in the brain[4][5][6].

The algorithm used by Nigam and Graupe, 2004 uses a multistage nonlinear preprocessing filter combined with an artificial neural network (ANN) for automatic detection of epileptic seizures on EEG signals [7]. Güler et al., 2005 used recurrent neural networks (RNNs) and Lyapunov feature extraction which was trained with the Levenberg-Marquardt algorithm[3]. Übeyli, 2006 uses a multilayer perceptron neural network (MLPNN). Übeyli, 2010 uses the Least-Square Support Vector Machine (LS-SVM) and the Autoregressive (AR) coefficient [8].

In this study, the method used is using Discrete Cosine Transform (DCT) and Backpropagatioan artificial neural networks. The first step uses cosine transform to convert /extract a signal into its basic frequency component so that several features are obtained to capture the specific characteristics of the EEG signal and then these features are used as input to Backpropagation to obtain a classification of detected epilepsy or nonepilepsy.

2. Methodology

In the EEG signal classification system there are three functions, namely first to perform pre-processing (input processing) input signals which will be used for learning data, second to extract EEG signals and the third to classify EEG signals identified by epilepsy and non epilepsy

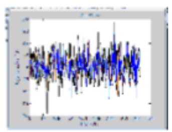
The epilesi and non-epilepsy identification system based on EEG signals in this study consisted of several stages of the process, the first taking EEG signals used as data for the learning process, the second stage was the process of extracting EEG signals using DCT[9] to obtain signal features that aim to bring out features and reduce the dimensions of the signal from the higher dimensions to the lower dimensions. The third stage of classification is to classify EEG signals detected by epilepsy and non-epilepsy based on similarity measurements using artificial neural network modeling Backpropagation method[10].

EEG signal data from the University of Bonn consists of five classes of datasets namely A, B, C, D, and E. Each dataset contains 100 single-channel EEG segments with a duration of 23.6 seconds[11]. Each segment is selected and cut from continuous multichannel EEG recordings after visual artifact inspection, such as eye movements or muscle activity. Sets A and B are signals taken from EEG records conducted on five healthy volunteers with a standard electrodes placement scheme (International 10-20 system). Volunteers are relaxed and awake with eyes open (for set A) and eyes closed (for set B). The C-E set is from the EEG archive for presurgical diagnosis. EEGs from five patients were selected, and all had achieved complete seizure control, after resection of one of the hippocampal formations, so that they were correctly diagnosed into the epileptogenic zone. Set D signals are recorded in the epileptogenic zone, and are at intervals without seizures and set C originates from the formation of the hippocampus in the opposite hemisphere of the brain. While sets C and D contain activities that are only measured during intervals without seizures, while sets E only contain seizure activities. The data set A and set E are used in this study. In accordance with existing references, all EEG signals are recorded with an amplifier system with 128 channels. Digitalization of data with a frequency of 173.61 samples per second using a 12-bit A / D converter. The passfilter band is set at 0.53 40 Hz (12 dB / oct). Each of the digital EEG signal data consists of 4097 discrete data. The EEG signal plots set A, B, C, D and set E used in this research are time series.

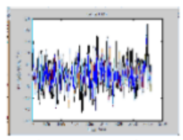
EEG signal data from the University of Bonn consists of five classes of datasets namely A, B, C, D, and E. Each dataset contains 100 single-channel EEG segments with a duration of 23.6 seconds[11]. Each segment is selected and cut from continuous multichannel EEG recordings after visual artifact inspection, such as eye movements or muscle activity. Sets A and B are signals taken from EEG records conducted on five healthy volunteers with a standard electrodes placement scheme (International 10-20 system). Volunteers are relaxed and awake with eyes open (for set A) and eyes closed (for set B). The

C-E set is from the EEG archive for presurgical diagnosis. EEGs from five patients were selected, and all had achieved complete seizure control, after resection of one of the hippocampal formations, so that they were correctly diagnosed into the epileptogenic zone. Set D signals are recorded in the epileptogenic zone, and are at intervals without seizures and set C originates from the formation of the hippocampus in the opposite hemisphere of the brain. While sets C and D contain activities that are only measured during intervals without seizures, while sets E only contain seizure activities. The data set A and set E are used in this study[11]. In accordance with existing references, all EEG signals are recorded with an amplifier system with 128 channels.

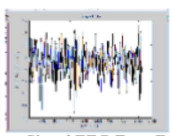
Digitalization of data with a frequency of 173.61 samples per second using a 12-bit A / D converter. The passfilter band is set at 0.53 40 Hz (12 dB / oct). Each of the digital EEG signal data consists of 4097 discrete data. The EEG signal plots set A, B, C, D and set E used in this research are time series.



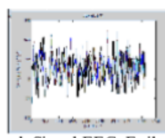
a. EEG Normal Terbuka



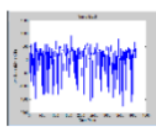
b.Sinyal EEG Normal Tertutup



a. Sinyal EEG Zona Epilepsi



d. Sinyal EEG Epilepsi



. e. Sinyal EEG Epilepsi Kejang

Figure 1. Five Class EEG Signals (A, B, C, D, E)

3. Extraction Process Using DCT

Discrete Cosinus Transform (DCT) is a technique used to convert signals into its forming frequency components. This transformation can be seen as a form of discrete time (discrete-time) of the fourier cosine transformation (Discrete Fourier Transform / DFT), unlike DFT, DCT only takes into account the real value of the transformed results and tends to have a fairly good approach to the original signal [9] .

Feature extraction is a stage to bring out features and reduce the dimensions of the image from the high dimensions to the lower dimensions. DCT can be used to carry out the EEG Signal extraction process which changes the function from the spatial domain to the basic frequency domain[9]. Discrete Cosine Transform represents an image of the sum of the sinusoid of varying magnitudes and frequencies. The nature of DCT is to change image information that is concentrated only on a few DCT coefficients, thus making the data represented in its frequency component[9].

Discrete Cosine Transform of a series of n real numbers s (x), x = 0, ..., n-1, formulated as Following.
(Watson1994):

$$S(u)\sqrt{\frac{2}{n}C(u)}\sum_{x=0}^{n-1} s(x)\left(\cos\frac{(2x+1)u\pi}{2n}\right)$$

$$C_k = \begin{cases} \frac{1}{\sqrt{2}}, k = 0 \\ 1, k > 0 \end{cases}$$

If K = 0, the formula used is :

$$W_k = \sum\nolimits_{t=0}^{n-1} a_t \cos\left[\frac{\pi}{n}\left(t+\frac{1}{2}\right)k\right], k = 0, \dots, n-1$$

And if K> 0, then the formula used is :

$$W_k = C_k\sqrt{\frac{2}{n}}\sum\nolimits_{t=0}^{n-1} a_t \cos\left[\frac{\pi}{n}\left(t+\frac{1}{2}\right)k\right] = \quad 0, \dots, n-1$$

The purpose of EEG signal extraction is to facilitate input data in the training process on the network. Furthermore, this study takes the value of 4096 data points on each EEG signal, after the DCT process is obtained visualization patterns that can be read and still produce data point values, namely data points 256.

EEG signal data taken from data sets A, set B, set C, set D data set E each of 100 EEG signals using a signal length of 4096 points each time series data. The next process is the DCT process by cutting the signal with a signal length of 256 signals for all dataset segments. So in the process of classification of epilepsy and non-epilepsy, the data length is 256 for each of the five class EEG signal segments.

Program Segment 3.1: The EEG Signal Extraction Process uses DCT for class A

```
 %Training data for class Z TO A
1.d01=load('E:\Tesis_Ade_Bab       3\ade\DATA SET\Z Set A\Z001.txt');
2.data_10=d01(1:256)
  figure(1)
  plot(data_10)
  % Transfer ke DCT
3.x1=dct(data_10)
  figure(2)
  plot(x1(:,1)); xlabel('Data  Point'); ylabel('Amplitudo  (Mikro  Volt)');
  title('Sinyal EEG TerDCT')
  % Transfer ke iDCT
4.x2=x1(1:256)
  x3=idct(x2)
  figure(3)
  plot(x3)
  xlabel('DataPoint');ylabel('Amplitudo (Mikro Volt)');
```

Program segment 3.1 explains the DCT process on the EEG Z001 signal with a signal length of 1500 using the data set A. In line 1 it picks up the EEG Z001 signal in the file storage folder. The second line initializes the signal to be DCT. The third line is the process of transferring EEG signals with a length of 256 using DCT. The fourth line is the DCT inverse transfer process to prove that the initial signal after the DCT has not changed. Processes in the two segment program are applied to five classes of EEG signal data sets.

4. EEG Signal Identification Using Backpropagation Artificial Neural Networks

Journal of Physics: Conference Series **1381** (2019) 012037 doi:10.1088/1742-6596/1381/1/012037

The data needed for the discussion of Backpropagation neural networks is the data from the feature extraction values from the DCT method. The feature extraction value data from the DCT method has variation data from five datasets taking a DCT value of 256 data points per EEG signal.

Network architecture that will be used in the learning process. The classification model is formed using Backpropagation Artificial Neural Network with Multi-layer architecture[12]. The number of input variables used in this study are 5 variables which are 5 different classes of data, where the researcher will make 3 structures of Artificial Neural Networks (ANN). The first ANN structure consists of two input variables, namely class A data of normal eye signal open) and class B (normal signal closed eyes), for the second ANN structure consisting of three input variables, namely class C data (entering epileptogenic zone), class D (when the epileptogenic zone) and class E (seizure activity), for the third ANN structure consists of two input variables namely class A data (normal signal open eye) and Class E (seizure activity).

At each layer of the ANN architecture also set some parameters that will be given in the learning process and tested to form a classification model. The activation function used in the hidden layer uses the trainlm, while the output layer uses the purelin activation function. The minimum error tolerance (error) is 0.00001, the learning rate is 0.1, the maximum number of epochs in this study is 1000.

Program segment 4.1: Training process (Learning)

```
% Training Process (learning)
% DATA FROM DCT 256 CIRI
1. a1=load('D:\ade\DATA SET\Z Set A\Data_DCT_T_256_100.txt')'
   b1=load('D:\ade\DATA SET\O SET B\Data_DCT_T_256_100.txt')'
   c1=load('D:\ade\DATA SET\N SET C\Data_DCT_T_256_100.txt')'
   d1=load('D:\ade\DATA SET\F SET D\Data_DCT_T_256_100.txt')'
   e1=load('D:\ade\DATA SET\S SET E\Data_DCT_T_256_100.txt')'
2.%Define inputs (combine samples from all three classes)
   aa=a1(1:256,1:80)
   bb=b1(1:256,1:80)
   cc=c1(1:256,1:80)
   dd=d1(1:256,1:80)
   ee=e1(1:256,1:80)
3. % Data Target
   a =[1];
   b = [1];
   c = [-1];
   d = [-1];
   e = [-1]';
4. % Define Targets
   P = [aa,bb,cc,dd,ee];
   T   =   [repmat(a,1,80)   repmat(b,1,80)   repmat(c,1,80)   repmat(d,1,80)
   repmat(e,1,80)];
5. %Membuat jaringan
   net=newff(minmax(P),[30,20,1])
   net.trainParam.lr=0.1
   net.trainparam.show=100;
   net.trainParam.epoch=1000
   net.trainParam.goal=0.00001
6. %Proses Training
   net=train(net,P,T);
   %Hasil Setelah Pelatihan
   w1= net.IW{1,1}
   w2= net.LW{2,1}
   w3= net.LW{3,2}
   b1=net.b{1}
```

```
   b2=net.b{2}
   b3=net.b{3}
7. save net.mat net
   y=sim(net,P)
    OutputLth=y'
```

Program Segment 4.1 explains the Training (learning) process in the ABCDE data set. In line 1 picks up the ABCDE data set signal in the file storage folder. The second line of signal initialization process will be in Training where the signal length used in each pattern is 256 and the data used in each class is 80 signal patterns. The third row is the initialization of the output layer value that will be generated, namely A (1), B (1), C (-1), D (-1) and E (-1). The fourth line is the expected target initialization process. The fifth line initializes the learning parameters used in the training process. The sixth line is the initialization of learning parameters used in the training process. Line 7 storage process value of the weights and bias values obtained in the training process. The process in segment one program is applied to the AB data set and CDE data set training processes.

Segmen program 4.2 : Proses Testing

%program Testing (uji coba)

```
1. %pemanggilan jaringan yang telah dilatih
   load net.mat
2. %proses membaca data yang diuji dari data set
   a1=load('D:\ade\DATA SET\Z Set A\Data_DCT_T_256_100.txt')'
   b1=load('D:\ade\DATA SET\O SET B\Data_DCT_T_256_100.txt')'
   c1=load('D:\ade\DATA SET\N SET C\Data_DCT_T_256_100.txt')'
   d1=load('D:\ade\DATA SET\F SET D\Data_DCT_T_256_100.txt')'
   e1=load('D:\ade\DATA SET\S SET E\Data_DCT_T_256_100.txt')'
3. %Define inputs (combine samples from all three classes)
   aaa=a1(1:256,81:100)
   bbb=b1(1:256,81:100)
   ccc=c1(1:256,81:100)
   ddd=d1(1:256,81:100)
   eee=e1(1:256,81:100)
   aaa1=aaa
   bbb1=bbb
   ccc1=ccc
   ddd1=ddd
   eee1=eee
   pa=[aaa1,bbb1,ccc1,ddd1,eee1]
4. % Define Output
   Y2=net(pa)
    out=Y2'
```

Program Segment 4.2 explains the Testing process in the ABCDE data set. In line 1 is the process of loading the weight and bias values of the training results. In the second line picks up the ABCDE data signal set in the file storage folder. In the third line the signal initialization process will be tested where the signal length used in each pattern is 256 and the data used in each class is 20 signal patterns. The fourth line is the process of testing output results. The process of the two segment program is applied to the process of testing AB data sets and CDE data sets.

Based on the testing process carried out with 2 Architecture namely the first architecture for ABCDE data sets, the second architecture for AB data sets and CDE sets, using a number of different hidden layers and layer nodes, the results of Identification of five classes of EEG signals can be seen as follows :

Table 1
Results of ABCDE Data Set Identification

	1 Hidden Layer	*2 Hidden Layer*	*3 Hidden Layer*
Time	*5: 03minutes : 04second*	*08: 56minutes : 23second*	*0: 38minutes : 03second*
Iterasi	*709*	*1000*	*38*
MSE	*9,84x 10-6*	*0,00431*	*7,01x 10-6*
Ketepatan	*74%*	*75%*	*76%*

Table 2
Results of Identification of AB and CDE Data Sets

	1 Hidden Layer	*2 Hidden Layer*	*3 Hidden Layer*
Time	*0: 56minutes : 54second*	*2: 51minutes : 42second*	*14:11minut es : 14second*
Iterasi	*132*	*114*	*1000*
MSE	*7,47 x 10-6*	*6,04 x 10-6*	*0,0112*
Ketepatan	*72%*	*73%*	*79%*

5. CONCLUSION
A careful analysis of the electroencephalogram (EEG) record can provide valuable information value to understand the mechanism behind epilepsy disorders. Since epileptic seizures occur irregularly and unexpectedly, automatic seizure detection in EEG records is needed. The results of this study indicate that with feature extraction using DCT and the identification process using Backpropagation Neural Networks, the test results obtained for the identification of EEG signal ABCDE class data sets by 75%, for AB and CDE class data sets by 73%.

6. BIBLIOGRAPHY
[1] Polat K and Güneş S 2007 Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform *Appl. Math. Comput.* **187** 1017–26
[2] Andrzejak R G, Lehnertz K, Mormann F, Rieke C, David P and Elger C E 2001 Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state *Phys. Rev. E - Stat. Physics, Plasmas, Fluids, Relat. Interdiscip. Top.* **64** 8
[3] Gu I 2005 Recurrent neural networks employing Lyapunov exponents for EEG signals classification **29** 506–14
[4] Adeli H, Ghosh-dastidar S and Dadmehr N 2006 A Wavelet-Chaos Methodology for Analysis of EEGs and EEG Sub-Bands to Detect Seizure and Epilepsy
[5] Subasi A 2007 EEG signal classification using wavelet feature extraction and a mixture of expert model **32** 1084–93
[6] Ataee P, Avanaki A N, Shariatpanahi H F and Khoee S M 2006 Ranking features of wavelet-decomposed EEG based on significance in epileptic seizure prediction *Eur. Signal Process. Conf.*
[7] Guo L, Rivero D, Dorado J, Rabuñal J R and Pazos A 2010 Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks *J. Neurosci. Methods* **191** 101–9

[8] Karyawan M A, Zainal A, Saikhu A, Teknologi I and Nopember S 2011 Klasifikasi Sinyal Eeg Menggunakan Koefisien Autoregresif , **2** 1–13
[9] Khayam S A 2003 (DCT):
[10] Güler I and Übeyli E D 2005 Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients *J. Neurosci. Methods* **148** 113–21
[11] Gautama T, Mandic D P and Van Hulle M M 2003 Indications of nonlinear structures in brain electrical activity *Phys. Rev. E - Stat. Physics, Plasmas, Fluids, Relat. Interdiscip. Top.* **67** 5
[12] Handayani L and Adri M 2015 Penerapan JST (Backpropagation) untuk Prediksi Curah Hujan (Studi Kasus : Kota Pekanbaru) 238–47

epilepsi deteksi

ORIGINALITY REPORT

9%	9%	13%	%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

MATCH ALL SOURCES (ONLY SELECTED SOURCE PRINTED)

8%
★ ethesis.nitrkl.ac.in
Internet Source

Exclude quotes	On	Exclude matches	< 2%
Exclude bibliography	On		