MÜHENDİSLİK FAKÜLTESİ

Uluslararası Mühendislik Araştırma ve Geliştirme Dergisi

International Journal of Engineering Research and Development

Cilt/Volume:9 Sayı/Issue:3 Aralık/December 2017 https://doi.org/10.29137/umagd.348871

Araştırma Makalesi / Research Article

Subject-Dependent and Subject-Independent Classification of Mental Arithmetic and Silent Reading Tasks

Mustafa Turan Arslan[1] , Server Goksel Eraldemir[2], Esen Yildirim[3]

[1]*Mustafa Kemal University, Hatay,31000,Turkey*
[2]*Iskenderun Technical University, Hatay, 31200, Turkey*
[3]*Adana Science and Technology University, Adana,1410,Turkey*

Başvuru/Received: 08/10/2017 **Kabul/Accepted**: 01/12/2017 **Son Versiyon/Final Version**: 26/12/2017

Abstract

In this study, the electrical activities in the brain were classified during mental mathematical tasks and silent text reading. EEG recordings are collected from 18 healthy male university/college students, ages ranging from 18 to 25. During the study, a total of 60 slides including verbal text reading and arithmetical operations were presented to the subjects. EEG signals were collected from 26 channels in the course of slide show. Features were extracted by employing Hilbert Huang Transform (HHT). Then, subject-dependent and subject-independent classifications were performed using k-Nearest Neighbor (k-NN) algorithm with parameters k=1, 3, 5 and 10. Subject-dependent classifications resulted in accuracy rates between 95.8% and 99%, whereas the accuracy rates were between 92.2% and 97% for subject independent classification. The results show that EEG data recorded during mathematical and silent reading tasks can be classified with high accuracy results for both subject-dependent and subject-independent analysis.

Key Words

"EEG classification, Hilbert Huang Transform, k-Nearest Neighbors"

*** mtarslan@mku.edu.tr***

1. INTRODUCTION

Studies on Human-Computer Interaction (HCI) systems increased rapidly in the last decade (Lughofer et al., 2009; Lughofer et al., 2011; Vézard et al., 2015). The goal of these systems is to provide interactive communication between humans and computers. Automatic voice response systems and search engines are some examples of above-mentioned systems. A specialized version of these systems is Brain-Computer Interface (BCI) in which the systems are driven by brain signals. These interfaces are extremely useful for specifically disabled individuals with difficulty of using their muscles or skeletal systems (Kottaimalai et al., 2013; Liao et al., 2014; Liao et al., 2012). In these systems, the analysis of the signals produced in the brain is performed, mostly, in real time. Electrical signals, magnetic field and hemodynamic changes that occur during the processes in brain can be measured by Electroencephalography (EEG), Magnetoencephalography (MEG) and Functional Magnetic Resonance Imaging (fMRI), modalities respectively. The most commonly used method in BCI systems is EEG due to its ease of use, mobility and low cost (Ruan et al., 2014; Schalk, 2008; Wolpaw et al., 2006).

EEG signals are non-stationary and non-linear signals like many other physiological signals (Kaplan et al., 2005; Lo et al., 2009). Wavelet Transform, which is known to be more effective in analyzing nonlinear signals, is widely used (Eraldemir & Yildirim, 2015; Handojoseno et al., 2013), although Fourier Transform (FT) is used in some studies (Dkhil et al., 2015; Samiee et al., 2015; Wang et al., 2016) in EEG signal analysis. A relatively new method, Hilbert Huang Transform (HHT), was proposed by Norden E. Huang in 1996. HHT is an adaptive and efficient signal processing method and it is convenient for processing non-linear and non-stationary signals (Huang et al., 1996). The method has been used for EEG feature extraction in many studies (Guang et al., 2005; Rahul Kumar Chaurasiya et al., 2015; Wang et al., 2015; Yang et al., 2006). HHT is used in areas such as detection of alcohol dependence (Lin et al., 2015), detection of automatic sleep level (Fraiwan et al., 2011; Liu et al., 2010), diagnosis (Bajaj & Pachori, 2013) and prediction (Ozdemir & Yildirim, 2014) of epileptic seizure, measurement of anesthesia depth (Shih et al., 2015) and BCI applications (Jerbic et al., 2015). k-Nearest Neighbor (k-NN) is one of the popular classification methods that have been used in many EEG signal classification studies. (Eraldemir et al., 2014) have classified mathematical tasks using wavelet-based features from EEG signals with k-NN classifier and have reported 79.3%, 74.9%, 72.4% and 68.6% accuracy for k=1, 3, 5, and 10 respectively. (Noshadi et al., 2014) used empirical mode decomposition and k-NN for cognitive tasks classification with 97.78 % accuracy. (Yazdani et al., 2009) used autoregressive (AR) models and wavelet decomposition transform for feature Extraction and k-NN for classification of EEG signals of five different mental tasks.

In this study, EEG signals collected during a slide show consisting of mental arithmetic operation and silent reading slides are classified by means of k-NN. Features used for classification are extracted using HHT methodology. Subject dependent and independent classification performances are presented. The rest of the paper is organized as follows. Section 2 briefly describes the collection of EEG data, extraction of features and classification algorithm. The classification results obtained by k-NN are given in Section 3 and the conclusion is given in Section 4.

2. MATERIALS AND METHOD

This section describes the details of the materials and methods used during experimental study, which include the experimental tasks, dataset description, Hilbert Huang Transform and description of classifier and the discussion of their performance parameters. The main steps used in the study is summarized in Fig. 1.

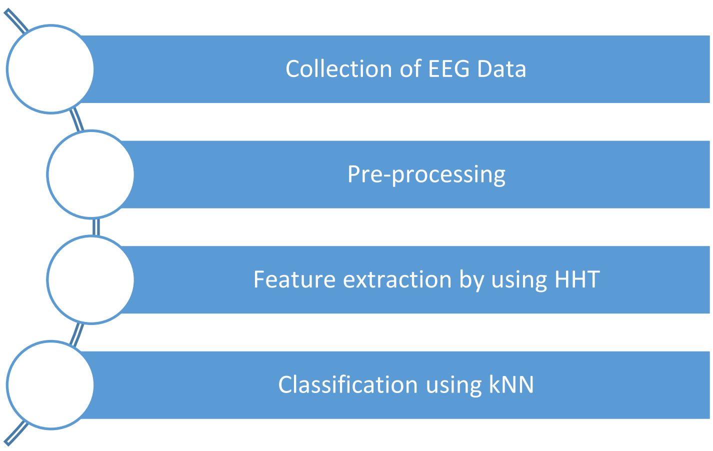

Fig. 1. The basic steps of the experimental study

2.1. Collection of EEG Data

In this study, EEG signals are collected from 18 voluntary healthy males who are university/college students. EEG electrodes were positioned according to the 10-20 international system and signals were collected from 22 electrodes forming 26 channels with a sampling frequency of 1 kHz.

26 channels which was used on EEG device are attained by using reference points. The names of those are Fp1-A1, Fp2-A2, F3-A1, F4-A2, C3-A1, C4-A2, P3-A1, P4-A2, O1-A1, O2-A2, F7-A1, F8-A2, T3-A1, T4-A2, T5-A1, T6-A2, Fp2-O2, Fp1-O1, Fp1-Fp2, F7-F8, F3-F4, T3-T4, C3-C4, T5-T6 P3-P4 and O1-O2, respectively.

Subjects were warned prior to the recording sessions about not to move their muscles, blink or swallow to minimize possible artefacts in EEG signals. EEG recordings were collected in a quiet and comfortable environment. In addition, subjects were asked to have short and clean hair and they were warned not to use any medical drug.

30 arithmetic and 30 verbal slides, each 13.25 seconds long, 5 were shown the subjects. Sample arithmetic and verbal slides are shown in Fig. 2. and Fig. 3., respectively.

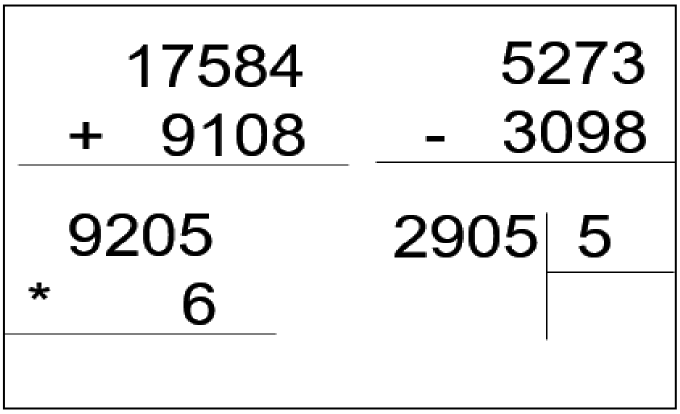

Fig. 2. The examples of numeric slide

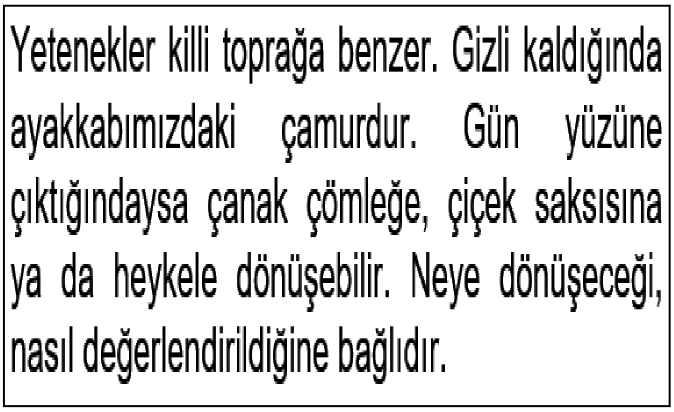

Fig. 3. The examples of verbal slide

The subjects were asked to focus on the arithmetic operation or reading the text instead of being in a rush to complete the process.

2.2. Feature Extraction

50 Hz line noise was directly cleaned by the EEG device and a band-pass filter between 0.5 and 120 Hz was applied to the EEG recordings. The first and the last slides were not used because of the synchronization problem in segmenting the raw EEG data. After this pre-processing step features are extracted using HHT.

HHT is presented by Huang et al. in 1996 (Huang et al., 1996). HHT associates Empirical Mode Decomposition (EMD) with well-known Hilbert transform to form the Hilbert spectrum. HHT is a more developed technique than other techniques such as Fourier Transform and Wavelet Transform, which expand the signal by predetermined basis functions. This technique is an adaptive data analysis method, which extracts the basis function from the data itself, designed privately for analyzing data from nonlinear and nonstationary signals.

The main step of the HHT is the EMD method with which a complicated data set can be decomposed into components named intrinsic mode functions (IMF). Hilbert transform is applied to the IMFs to obtain the energy-frequency-time distribution, designated as Hilbert spectrum.

The instantaneous frequencies can be calculated by means of the Hilbert Transform, with which any real valued function x(t) can be presented as an analytic function, z(t), with the complex part, y(t) computed as:

$$y(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} \tag{1}$$

where the P represents the Cauchy principle value of the singular integral. Finally the analytic function is:

$$z(t) = x(t) + jy(t) = a(t)e^{j\theta(t)} \tag{2}$$

where

$$a(t) = (x^2 + y^2)^{1/2} \;;\; \theta(t) = \tan^{-1}\frac{y}{x} \tag{3}$$

Here a is the instantaneous amplitude, and θ is the phase function; and the instantaneous frequency is indicated as follows.

$$\omega = -\frac{d\theta}{dt} \tag{4}$$

2.3. Classification

EEG signals collected during mental mathematical operations and silent readings are classified using a k Nearest Neighbor (k-NN). The k-NN algorithm is one of the machine learning algorithms used in many fields (Cover & Hart, 1967). The algorithm is also a simple and intuitive method of classifier used by many researchers typically for classifying EEG signals. The k-NN classification is based on finding closest training samples to a test sample and assigning it to the most dominant class.

We need to specify the value of "k" closest neighbor for binary classification. In this experiment, we try different "k" values ranging from 1 to 10, namely 1, 3, 5 and 10. "Euclidean" distance measure is used in order to calculate distance between test sample and training samples in the feature space.

$$d(p,q) = \sqrt{\sum_{i=1}^{n} \left(p_i - q_i\right)^2} \tag{5}$$

where $d(p,q)$ is the distance between the samples p and q, n represents the number of features and the ith feature of the sample are described as p_i and q_i, respectively (Ahangi et al., 2013).

3. RESULTS AND DISCUSSION

In this study, we considered the effect of HHT and k-NN method on classification result, considering that HHT based features show better classification performance. The features were obtained by using HHT from EEG signals and these features were binary classified as mathematical operation / verbal reading using k-NN algorithm.

The performance of k-NN was computed using the most commonly used parameters such as accuracy, precision and f-measure (Subasi & Gursoy, 2010).

The values of k in the k-NN algorithm used in the study were selected as 1, 3, 5, and 10. The 10 fold cross-validation approach was used in an attempt to test to performance of k-NN algorithm. The results were compared as both subject-dependent and subject-independent. The results of subject-dependent studies are shown in Table 1-4.

The classification results of 26-channel EEG data are given in Table 1 for k = 1. Examining Table 1, it is seen that the number of subjects with accuracy of 99% and above is 11. The lowest accuracy rate is 94.80% for the subject 3 while the highest accuracy rate was 99.9% for the subject 14 and subject 15. The average accuracy rate of 18 subjects was 99.01%. In addition, there are two subjects with 99.9% accuracy in this table. In analysis of 26-channel EEG data, precision and f-measure were 99.01% and 99.01%, respectively on the average.

Table 1: The results of subject-dependent with k=1

1-NN			
No of Subject	**Accuracy**	**Precision**	**F-Measure**
Subject1	0.984	0.984	0.984
Subject2	0.987	0.987	0.987
Subject3	0.948	0.949	0.948
Subject4	0.987	0.987	0.987
Subject5	0.996	0.996	0.996
Subject6	0.988	0.988	0.988
Subject7	0.996	0.996	0.996
Subject8	0.998	0.998	0.998
Subject9	0.990	0.990	0.990
Subject10	0.993	0.993	0.993
Subject11	0.987	0.987	0.987
Subject12	0.997	0.997	0.997
Subject13	0.996	0.996	0.996
Subject14	0.999	0.999	0.999
Subject15	0.999	0.999	0.999
Subject16	0.988	0.988	0.988
Subject17	0.992	0.992	0.992
Subject18	0.996	0.996	0.996

Table 2 shows the results when the k parameter is selected as 3. The k-NN algorithm yielded the highest performance for the subject 7 with the accuracy of 99.7%. The average classification performances of EEG data with 18 subjects was found as 97.72%, 97.75% and 97.72% with accuracy, precision and f-measure, respectively. Table 2 demonstrated that there are only 6 subjects whose performance are 99% or above for accuracy.

Table 2: The results of subject-dependent with k=3

3-NN			
No of Subject	**Accuracy**	**Precision**	**F-Measure**
Subject1	0.966	0.966	0.966
Subject2	0.964	0.965	0.964
Subject3	0.901	0.905	0.901
Subject4	0.973	0.973	0.973
Subject5	0.993	0.993	0.993
Subject6	0.968	0.968	0.968
Subject7	0.997	0.997	0.997
Subject8	0.990	0.990	0.990
Subject9	0.971	0.971	0.971
Subject10	0.982	0.982	0.982
Subject11	0.973	0.973	0.973

Table 2 (Cont): The results of subject-dependent with k=3

3-NN			
No of Subject	**Accuracy**	**Precision**	**F-Measure**
Subject12	0.988	0.988	0.988
Subject13	0.991	0.991	0.991
Subject14	0.994	0.994	0.994
Subject15	0.996	0.996	0.996
Subject16	0.972	0.972	0.972
Subject17	0.984	0.984	0.984
Subject18	0.987	0.987	0.987

As can be seen from Table 3, the subject 7 has the best performance metrics with %99.4 while the subject 3 has the worst achievement on accuracy, precision and f-measure with 87.9%, 88.6% and 87.8%, respectively. In addition, the average accuracy, precision and f-measure were 96.75%, 96.79% and 96.74%, respectively. It is also worth to note that, k=5 resulted in 99% or above accuracy for only 3 subjects.

Table 3: The results of subject-dependent with k=5

5-NN			
No of Subject	**Accuracy**	**Precision**	**F-Measure**
Subject1	0.950	0.950	0.950
Subject2	0.938	0.939	0.938
Subject3	0.879	0.886	0.878
Subject4	0.969	0.969	0.969
Subject5	0.985	0.985	0.985
Subject6	0.943	0.943	0.943
Subject7	0.994	0.994	0.994
Subject8	0.983	0.983	0.983
Subject9	0.963	0.963	0.963
Subject10	0.972	0.972	0.972
Subject11	0.967	0.967	0.967
Subject12	0.973	0.973	0.973
Subject13	0.987	0.987	0.987
Subject14	0.992	0.992	0.992
Subject15	0.990	0.990	0.990
Subject16	0.966	0.966	0.966
Subject17	0.978	0.978	0.978
Subject18	0.986	0.986	0.986

Table 4 shows that k-NN algorithm achieved the best results on subject7 when the value of k was selected as 10. Subject3 has the poorest performance values with 85.9%, 86.7% and 85.8% for accuracy, precision and f-measure respectively. In addition, the average accuracy of 95.81% was obtained. The results show that there is no subject with an accuracy of 99% or above for k=10.

Table 4: The results of subject-dependent with k=10

10-NN			
No of Subject	**Accuracy**	**Precision**	**F-Measure**
Subject1	0.941	0.941	0.941
Subject2	0.921	0.923	0.921
Subject3	0.859	0.867	0.858
Subject4	0.967	0.967	0.967
Subject5	0.979	0.979	0.979
Subject6	0.932	0.932	0.932
Subject7	0.988	0.988	0.988
Subject8	0.970	0.970	0.970
Subject9	0.956	0.957	0.956
Subject10	0.964	0.964	0.964
Subject11	0.950	0.951	0.950
Subject12	0.965	0.965	0.965
Subject13	0.981	0.982	0.981
Subject14	0.984	0.984	0.984
Subject15	0.982	0.982	0.982
Subject16	0.957	0.957	0.957
Subject17	0.970	0.970	0.970
Subject18	0.980	0.980	0.980

It is demonstrated that the best classification results are obtained for k = 1 in subject-dependent study, and EEG signals recorded during mathematical and silent reading tasks are classified with an accuracy of %99.01 on average.

In this study, EEG signals were also classified as subject-independent using k-NN algorithm. In a subject independent study, training and testing are performed on EEG data that are collected from a group of subjects, whereas for subject dependent study these procedures are performed on only one subject's recordings. The values of 'k' is considered as 1, 3, 5 and 10 for subject independent study as in subject dependent studies for comparison purposes.

As it is shown in Table 5, k-NN algorithm performs very well on this dataset, with 99.01% for accuracy, precision and f-measure for k=1 in subject-dependent study on average.

Table 5: The average results of subject-dependent analysis

k	Accuracy	Precision	F-Measure
1	0.9901	0.9901	0.9901
3	0.9772	0.9775	0.9772
5	0.9675	0.9679	0.9674
10	0.9581	0.9588	0.9581

Table 6 shows that the best accuracy is achieved as 97.02% for k=1, as for the subject dependent case. As expected, subject dependent studies resulted in better accuracy values since each subject is trained with and tested on their own recordings. Nevertheless, the results achieved for subject–independent study are substantial.

Table 6: The results of subject-independent analysis

k	Accuracy	Precision	F-Measure
1	0.9702	0.9702	0.9702
3	0.9492	0.9494	0.9493
5	0.9389	0.9390	0.9390
10	0.9225	0.9225	0.9225

It is clearly seen that the HHT-based features extracting during mental arithmetic and silent reading tasks are classified with high accuracy for both subject-dependent and subject-independent analysis.

4. CONCLUSION

In this paper we have presented an approach to cognitive tasks based on the processing of EEG. The study presented the use of Hilbert Huang transform along with machine learning algorithms for the classification of spontaneous EEG signals recorded during a cognitive tasks.

For classification, k-NN was employed and its performance was evaluated for cognitive task discrimination. The classification results of k-NN demonstrated above 97% accuracy with features extracted using HHT method. The Hilbert transform is a powerful and useful tool to classify the EEG signals corresponding to complex cognitive tasks, and it will be helpful for EEG classification in clinical applications, such as epilepsy, depression, and stress diagnosis.

REFERENCES

Ahangi, A., Karamnejad, M., Mohammadi, N., Ebrahimpour, R., & Bagheri, N. (2013). Multiple classifier system for EEG signal classification with application to brain–computer interfaces. *Neural Computing and Applications*, *23*(5), 1319–1327. https://doi.org/10.1007/s00521-012-1074-3

Bajaj, V., & Pachori, R. B. (2013). Epileptic seizure detection based on the instantaneous area of analytic intrinsic mode functions of EEG signals. *Biomedical Engineering Letters*, *3*(1), 17–21. https://doi.org/10.1007/s13534-013-0084-0

Ben Dkhil, M., Wali, A., & Alimi, A. M. (2015). Drowsy driver detection by EEG analysis using Fast Fourier Transform. In *2015 15th International Conference on Intelligent Systems Design and Applications (ISDA)* (pp. 313–318). IEEE. https://doi.org/10.1109/ISDA.2015.7489245

Cover, T., & Hart, P. (1967). Nearest neighbor pattern classification. *IEEE Transactions on Information Theory*, *13*(1), 21–27. https://doi.org/10.1109/TIT.1967.1053964

Eraldemir, S. G., & Yildirim, E. (2015). Comparison of wavelets for classification of cognitive EEG signals. In *2015 23nd Signal Processing and Communications Applications Conference (SIU)* (pp. 1381–1384). IEEE. https://doi.org/10.1109/SIU.2015.7130099

Fraiwan, L., Lweesy, K., Khasawneh, N., Fraiwan, M., Wenz, H., & Dickhaus, H. (2011). Time Frequency Analysis for Automated Sleep Stage Identification in Fullterm and Preterm Neonates. *Journal of Medical Systems*, *35*(4), 693–702. https://doi.org/10.1007/s10916-009-9406-2

Handojoseno, A. M. A., Shine, J. M., Nguyen, T. N., Tran, Y., Lewis, S. J. G., & Nguyen, H. T. (2013). Using EEG spatial correlation, cross frequency energy, and wavelet coefficients for the prediction of Freezing of Gait in Parkinson's Disease patients. In *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 4263–4266). IEEE. https://doi.org/10.1109/EMBC.2013.6610487

Huang, N. E., Long, S. R., & Shen, Z. (1996). The Mechanism for Frequency Downshift in Nonlinear Wave Evolution. *Advances in Applied Mechanics*, *32*, 59–117C. https://doi.org/10.1016/S0065-2156(08)70076-0

Jerbic, A. B., Horki, P., Sovilj, S., Isgum, V., & Cifrek, M. (2015). Hilbert-Huang Time-Frequency Analysis of Motor Imagery EEG Data for Brain-Computer Interfaces (pp. 62–65). Springer, Cham. https://doi.org/10.1007/978-3-319-11128-5_16

Kaplan, A., Fingelkurts, A., Fingelkurts, A., & Borisov, S. (2005). Nonstationary nature of the brain activity as revealed by EEG/MEG: methodological, practical and conceptual challenges. *Signal Processing*, *85*(11), 2190–2212. Retrieved from http://www.sciencedirect.com/science/article/pii/S0165168405002094

Kottaimalai, R., Rajasekaran, M. P., Selvam, V., & Kannapiran, B. (2013). EEG signal classification using Principal Component Analysis with Neural Network in Brain Computer Interface applications. In *2013 IEEE International Conference ON Emerging Trends in Computing, Communication and Nanotechnology (ICECCN)* (pp. 227–231). IEEE. https://doi.org/10.1109/ICE-CCN.2013.6528498

Liao, F., Zhang, C., Bian, Z., Xie, D., Kang, M., Li, X., … Yi, M. (2014). Characterizing Heat-Sensitization Responses in Suspended Moxibustion with High-Density EEG. *Pain Medicine*, *15*(8), 1272–1281. https://doi.org/10.1111/pme.12512

Liao, L.-D., Chen, C.-Y., Wang, I.-J., Chen, S.-F., Li, S.-Y., Chen, B.-W., … Lin, C.-T. (2012). Gaming control using a wearable and wireless EEG-based brain-computer interface device with novel dry foam-based sensors. *Journal of NeuroEngineering and Rehabilitation*, *9*(1), 5. https://doi.org/10.1186/1743-0003-9-5

Lin, C.-F., Su, J.-Y., & Wang, H.-M. (2015). Hilbert-Huang Transformation Based Analyses of FP1, FP2, and Fz Electroencephalogram Signals in Alcoholism. *Journal of Medical Systems*, *39*(9), 83. https://doi.org/10.1007/s10916-015-0275-6

Liu, Z.-W., Faraguna, U., Cirelli, C., Tononi, G., & Gao, X.-B. (2010). Direct Evidence for Wake-Related Increases and Sleep-Related Decreases in Synaptic Strength in Rodent Cortex. *Journal of Neuroscience*, *30*(25), 8671–8675. https://doi.org/10.1523/JNEUROSCI.1409-10.2010

Lo, M.-T., Tsai, P.-H., Lin, P.-F., Lin, C., & Hsin, Y. L. (2009). The Nonlinear and Nonstationary Properties in EEG Signals: Probing The Complex Fluctuations by Hilbert–Huang Transform. *Advances in Adaptive Data Analysis*, *1*(3), 461–482. https://doi.org/10.1142/S1793536909000199

Lughofer, E., Bouchot, J.-L., & Shaker, A. (2011). On-line elimination of local redundancies in evolving fuzzy systems. *Evolving Systems*, *2*(3), 165–187. https://doi.org/10.1007/s12530-011-9032-3

Lughofer, E., Smith, J. E., Tahir, M. A., Caleb-Solly, P., Eitzinger, C., Sannen, D., & Nuttin, M. (2009). Human–Machine Interaction Issues in Quality Control Based on Online Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *39*(5), 960–971. https://doi.org/10.1109/TSMCA.2009.2025025

Meng Hu, Guang Li, Qiuping Ding, & Jiaojie Li. (2005). Classification of Normal and Hypoxia EEG Based on Hilbert Huang Transform. In *2005 International Conference on Neural Networks and Brain* (Vol. 2, pp. 851–854). IEEE. https://doi.org/10.1109/ICNNB.2005.1614755

Ozdemir, N., & Yildirim, E. (2014). Patient specific seizure prediction system using Hilbert spectrum and Bayesian networks classifiers. *Computational and Mathematical Methods in Medicine*, *2014*, 572082. https://doi.org/10.1155/2014/572082

Rahul Kumar Chaurasiya, R. K., Jain, K., Goutam, S., & Manisha. (2015). Epileptic seizure detection using HHT and SVM. In *2015 International Conference on Electrical, Electronics, Signals, Communication and Optimization (EESCO)* (pp. 1–6). IEEE. https://doi.org/10.1109/EESCO.2015.7253660

Ruan, X., Kun Xue, & Mingai Li. (2014). Feature extraction of SSVEP-based brain-computer interface with ICA and HHT method. In *Proceeding of the 11th World Congress on Intelligent Control and Automation* (pp. 2418–2423). IEEE. https://doi.org/10.1109/WCICA.2014.7053100

Samiee, K., Kovacs, P., & Gabbouj, M. (2015). Epileptic Seizure Classification of EEG Time-Series Using Rational Discrete Short-Time Fourier Transform. *IEEE Transactions on Biomedical Engineering*, *62*(2), 541–552. https://doi.org/10.1109/TBME.2014.2360101

Schalk, G. (2008). Brain–computer symbiosis. *Journal of Neural Engineering*, *5*(1), P1–P15. https://doi.org/10.1088/1741-2560/5/1/P01

Shih, M.-T., Doctor, F., Fan, S.-Z., Jen, K.-K., & Shieh, J.-S. (2015). Instantaneous 3D EEG Signal Analysis Based on Empirical Mode Decomposition and the Hilbert–Huang Transform Applied to Depth of Anaesthesia. *Entropy*, *17*(3), 928–949. https://doi.org/10.3390/e17030928

Subasi, A., & Ismail Gursoy, M. (2010). EEG signal classification using PCA, ICA, LDA and support vector machines. *Expert Systems with Applications*, *37*(12), 8659–8666. https://doi.org/10.1016/j.eswa.2010.06.065

Vézard, L., Legrand, P., Chavent, M., Faïta-Aïnseba, F., & Trujillo, L. (2015). EEG classification for the detection of mental states. *Applied Soft Computing*, *32*, 113–131. https://doi.org/10.1016/j.asoc.2015.03.028

Wang, M., Lv, Y., Wen, M., He, S., & Wang, G. (2016). A Fan Control System Base on Steady-State Visual Evoked Potential. In *2016 International Symposium on Computer, Consumer and Control (IS3C)* (pp. 81–84). IEEE. https://doi.org/10.1109/IS3C.2016.31

Wang, R., Wang, Y., & Luo, C. (2015). EEG-Based Real-Time Drowsiness Detection Using Hilbert-Huang Transform. In *2015 7th International Conference on Intelligent Human-Machine Systems and Cybernetics* (pp. 195–198). IEEE. https://doi.org/10.1109/IHMSC.2015.56

Wolpaw, J. R., Loeb, G. E., Allison, B. Z., Donchin, E., Do Nascimento, O. F., Heetderks, W. J., … Turner, J. N. (2006). BCI Meeting 2005—Workshop on Signals and Recording Methods. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *14*(2), 138–141. https://doi.org/10.1109/TNSRE.2006.875583

Yang, Z., Yang, L., & Qi, D. (2006). Detection of Spindles in Sleep EEGs Using a Novel Algorithm Based on the Hilbert-Huang Transform. In *Wavelet Analysis and Applications* (pp. 543–559). Basel: Birkhäuser Basel. https://doi.org/10.1007/978-3-7643-7778-6_40