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CLASSIFICATION OF EEG-BASED HAND GRASPING IMAGINATION USING AUTOREGRESSIVE AND NEURAL NETWORKS

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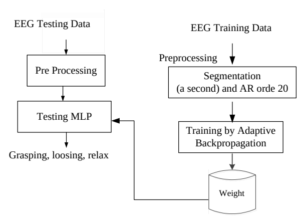
Graphical abstract



Abstract

In the development of Brain Computer Interface (BCI), one important issue is the classification of hand grasping imagination. It is helpful for realtime control of the robotic or a game of the mind. BCI uses EEG signal to get information on the human. This research proposed methods to classify EEG signal against hand grasping imagination using Neural Networks. EEG signal was recorded in ten seconds of four subjects each four times that were asked to imagine three classes of grasping (grasp, loose, and relax). Four subjects used as training data and four subjects as testing data. First, EEG signal was modeled in order 20 Autoregressive (AR) so that got AR coefficients being passed Neural Networks. The order of the AR model chosen based optimization gave a small error that is 1.96%. Then, it has developed a classification system using multilayer architecture and Adaptive Backpropagation as training algorithm. Using AR made training of the system more stable and reduced oscillation. Besides, the use of the AR model as a representation of the EEG signal improved the classification system accuracy of 68% to 82%. To verify the performance improvement of the proposed classification scheme, a comparison of the Adaptive Backpropagation and the conventional Backpropagation in training of the system. It resulted in an increase accuracy of 76% to 82%. The system was validated against all training data that produced an accuracy of 91%. The classification system that has been implemented in the software so that can be used as the brain computer interface.

Keywords: Grasping Imagination, brain computer interface, autoregressive, adaptive backpropagation

1.0 INTRODUCTION

Brain Computer Interface (BCI) establishes a direct communication pathway between the brain and an external device. Some BCI functions are help person who has a sensory-motor damage or developtment a game that is controlled of the mind. BCI translates the neural activities of the brain to control commands for driving external effectors such prosthetic device. This information can be extracted from Electroencephalogram (EEG) signal recordings. EEG is an instrument for capturing electrical activity in the brain, which also reflects the condition of mind. Direct visual observation of EEG signal is very difficult due to its low amplitude and complex pattern. Moreover, EEG signal is non-stationary and random, increasing the complexity in EEG signal analysis.

An important issue in designing a BCI is variables of mental task imagined. Among of them are attention, emotion, alertness, and hand grasping. Pattern of frequencies and amplitudes of the EEG can be used to classify toward its mental task variable. Grasping is one of the most fundamental ways humans interact with machine. Classification of grasping imagination is an interesting issue. It can be used for someone who has problem disability or robot control. Some classes are used in the previous research. They are holding, relax, quickly grasping and release rapidly [1]. Other research used the movement of "turn right" and "turn left" [2], writing and imagination writing [3] writing and grasping [4], hand grasping, opening and the resting state [5], imagination of the hand grasping, hand opening, and hands reaching [6], neural prosthesis hand system driven [7].

Some research used other mental variable, such identified mental activity [8, 9], human attention [10], emotion state [11-13], mental fatigue [14], and alertness level [15-17]. Moreover the classification of EEG signals has been carried out to recognize audio visual stimulation [18], sound stimulation [19, 20].

In developing the classification system, the EEG signals needs to be modeled according to the variable are reviewed. Transformation of EEG signal into a model is an effective way in analyzing EEG signal for classification purpose. EEG signal generally consists of wave components differentiated by their frequency range, which are alpha wave (8-13 Hz), very often appears in consciousness, closed eyes, and relax states; beta wave (14-30 Hz), highly observed during state of thinking; theta wave (4-7 Hz), generally exists when people take a nap, sleepy, or are in emotional stress; and delta wave (0.5-3 Hz), the main feature of brain activity when people are in deep sleep. Previous research used frequency components to extract EEG signals. It was also useful to eliminate noise, artifact or other noise information, thus the research used 5-30 Hz frequency of the signal acquired with 256 Hz sampling frequency. Some of them recognize of human grasping [1] human attention using FFT [10] emotion state using power spectral density [12], influence of sound stimulation using wavelet [19, 20] monitoring of alertness used power spectrum [17].

This research is a continuation of previous research in the identification of EEG signals toward mental task. Last research used alertness state using wavelet and neural network [15], two mental tasks using spectral wavelet [19], [20]. This research used imagine of hand grasping that are three classes, i.e. grasping, release, and relax. EEG signal was modeled in Autoregressive (AR). Thus, the AR coefficients as input of classification system using a multilayer perceptron (MLP)architecture. AR model has been widely used for EEG analysis. It is a linear combination of ICA and past EEG which brings the present EEG. Some research has used AR order 6 to model the EEG signals against the five mental tasks [21], identifying imagination of writing using AR and MLP with 91% accuracy [3] AR modelling [22], person identification using AR [23]. There are some methods in the identification of the EEG signal, including SVM and neural network with MLP network. Several previous research used MLP, such as imagination of three states of grasping with spectral analysis to pre-process [1], alertness state that used wavelet as a model [15], identification of emotional toward music stimulation [24].

In this research used 20-order AR coefficients of the channel FP1 every second. It became inputs of the MLP network with two hidden layers. AR coefficients represent generalization signals on certain imagination task. The EEG signal recorded in ten second by wireless Neurosky EEG of four subjects as data training and four students as data testing. Each recording was divided into five segments with stationer signal consideration. Identification system used MLP networks with an Adaptive Backpropagation algorithm in training. Using Adaptive Backpropagation algorithm intended to increase convergence speed and to minimize the error. It is done by dnamic learning rate [25].

2.0 MATERIAL AND PROPOSED METHOD

This research classified EEG signals using AR and MLP. EEG signals were recorded using 512 Hz sampling frequency, by four subjects as training data and four subjects are used as testing data. It is illustrated by Figure 1.

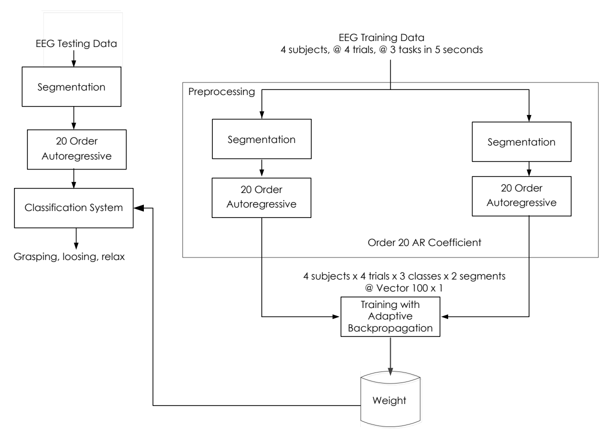


Figure 1 Classification system of EEG signal

2.1 EEG Data Acquisition

EEG signal recorded of eight subject 20-22 years old, student, and healthy. The subjects are conditioned adequate rest and not sleepy before experiment. The subjects were recorded in a sitting position with dim lighting levels (<0.05 lux). Room temperature ranging from about 20° C. Subject asked to imagination three state of grasping, i.e. grasping, loosing, and relax. It is illustrated by Figure. 2.

Each subject recorded in 35 seconds, imagine one of three grasp state in five seconds and 10 seconds of blank, as illustrated Figure 3.

Figure 2 EEG Recording in 35 seconds

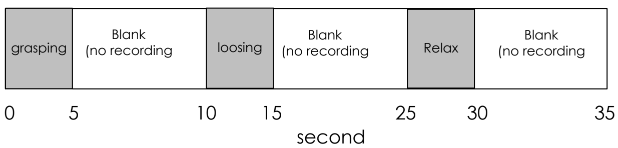


Figure 3 Recording in 35 seconds

Every recording was divided into two segments. Each segment was a set of data. Therefore, the total available 4 subject x 4 trial x 3 class x 2 segment = 96 sets as training data.

2.2 EEG Data Extraction by Autoregressive

The basic idea of autoregressive (AR) model is the assumption that the amplitude of EEG signal at n sample point can be approximated in AR process. It means prediction signal x (n + 1) based on previous information signal x (n), x (n-1), ..., x (n-k and certain error e(n). The AR model specifies that the output variable depends linearly on its own previous values and on a stochastic term thus the model is in the form of a stochastic difference equation So that the order and the coefficient of the approximation AR model are chosen in a way to fit the measured EEG as closely as possible. For every particular AR model, it provides an alternative way for EEG spectral properties. A real valued, zero mean, stationary, nondeterministic, AR process of order p is given by

$$x(n) = -\sum_{k=1}^{p} C_k x(n-k) + e(n) \tag{1}$$

where p is the model order, x(n) is the signal at the sampled point n, Ck are the real valued AR coefficients and e(n) represents an error that is independent of past samples. The term of autoregressive implies that the process x(n) was regressed upon previous samples. The error term is assumed to be a zero mean noise with finite variance, σ_p^2. In applications, the values of C_k and σ_p^2 have to be estimated from finite samples of data x(1), x(2), x(3), … ,x(n). In this paper was used Burg's method to estimate the AR coefficients. In this research using the order of 20 with quite consideration than a sampling frequency of 512 Hz [26]. The signal converted to 20 AR coefficients as feature extraction each second. When there were five segments, hence obtained 100 AR coefficients as input neural networks.

2.3 Classification System Using Multilayer Perceptron

This research used multilayer perceptron (MLP) for the classification network, which composed of an input layer, two hidden layer and output layer. Input layer has 100 neurons and output layer has three neurons. Input neurons were received by the AR coefficient in five seconds. Meanwhile, the first hidden layer has 20 neurons, and amount of the second hidden layer (zz) defined as the root of (hidden layer 1 x output layer) that is 8, as in Figure 4.

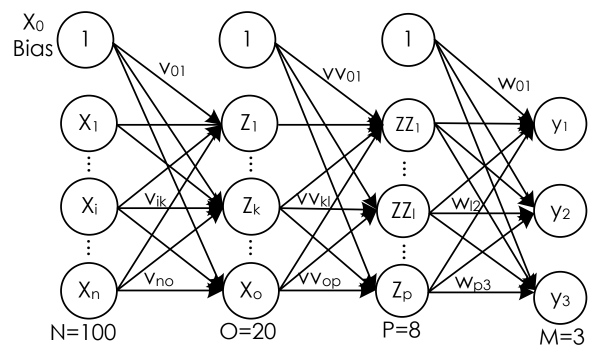


Figure 4 Multilayer Perceptron Networks

Each neuron of output layer is calculated as (2):

$$y_{net_k} = w_{ok} + \sum_{i=1}^{n} zz_l w_{lk} \tag{2}$$

Signal of output layer was calculated by activation function sigmoid biner as (3)

$$y_k = f(y_{net_k}) = \frac{1}{1+e^{-y_{net_k}}} \tag{3}$$

Backpropagation minimazed error between actual output (y_k) and desired output (d_k) for a pattern M:

$$e_k^{\,1} = y_k - d_k \tag{4}$$

$$e_k^{\,11} = (ly_k - y_k) \tag{5}$$

where

$$ly_k = f'(y_k)$$

Then all the linear and nonlinear errors of the neurons are multiplied with the derivative of the corresponding neuron's activation function and added separately as shown Eq (6):

$$\delta_1 = \sum_{k=1}^{M} e_k^{\,1} f^{'}(y_k) \qquad (6)$$

$$\delta_2 = \sum_{k=1}^{M} e_k^{\,11} f^{'}(y_k) \qquad (7)$$

$$\delta = (\delta_1 + \delta_2)/M \qquad (8)$$

Then adaptive learning rate are multiplied with the derivative of the corresponding neuron's activation function and added separately as shown Eq (9):

$$\mu_{out} = f'(\delta) \qquad (9)$$

where f is sigmoid activation function given by

$$f(\delta) = \frac{1}{1+e^{-\delta}} \qquad (10)$$

With property

$$f' = f(\delta)(1 - f(\delta)) \qquad (11)$$

Signal of hidden layer activation function was calculated by activation function sigmoid biner.

Then the change of weights are calculated using

$$\Delta w = \mu_{out} e_k^{'} f'(y_k) zz_l + \mu_{out} \lambda e^{11} ZZ_l \qquad (12)$$

As Adaptive Backpropagation

3.0 RESULTS AND DISCUSSION

3.1 EEG Signal Extraction

EEG signal was record in 512 Hz frequency sampling, that a second as shown in Table 1.

Table 1 EEG Signal in a Second

No	t(sampling)	Amplitude of Channel (FP1)
1	0.00195313	15
2	0.02539063	25
3	0.04687500	33
	…	…
512	1.00000000	-14

EEG signal per second, represented in AR model using the Equation (1) with 5 points overlapping. Then, using linear equation solution gave order 20 AR coefficienta as Table 2.

Table 2 AR Coefficients in a Second

No	Coefficient
1	0.17544
2	0.21875
3	-2.09091
4	0.09766
5	0.77316
6	0.10377
....	....
20	-0.33941

Reconstruction of EEG signals by the AR model compared to the original signal, as shown in Figure 5.

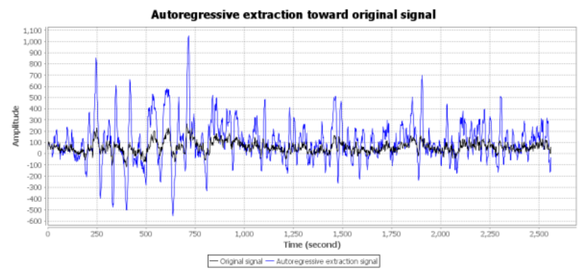


Figure 5 AR Model compared to original signal

Figure 5 showed that the reconstruction of the EEG signal of order 20 AR model gave similarities to original signal with 1.96% error. Then, the AR coefficients of five seconds passed neural networks classification.

3.2 Classification System

In this section we compared between outputs of system to real condition each segment and each subject. They are 4 subject x 4 trial x 3 class x 2 segment = 96 sets. System testing divided into three sections, which is: optimization of parameters (learning rate, MSE targets and the number of neurons in the hidden layer). Second, accuracy testing using AR model as a pre-process. Third, testing using AR model and Adaptive Backpropagation.

3.2.1 Optimization of Parameter

Using neural networks is dependent on the selection the coefficient of learning, learning method, and Mean Square Error (MSE). It is compared some parameter that gave accuracy as Table 3.

Table 3 Optimization of parameter

Fixed Learning Rate	Accuracy (%) of training data		
	MSE= 0.09	MSE = 0.2	MSE = 0.3
0.02	81%	63%	51%
0.1	91%	82%	61%
0.2	62%	70%	50%

We got learning rate 0.1 and tolerance of MSE 0.01 was 91% accuracy with 15 minutes training. MSE decreased in epoch as shown Figure 6. Using Adaptive Backpropagation as a learning method, which aims to increase convergence and reduce errors compared conventional Backpropagation, as shown Figure 6.

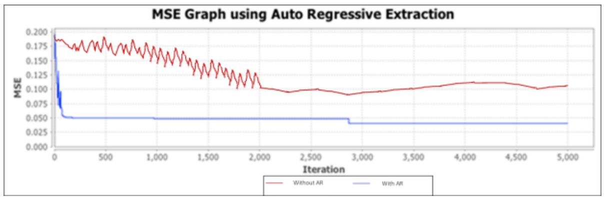


Figure 6 MSE Learning

3.2.2 Using AR Extraction

Identification system was tested the performance against using AR model. Using AR model improved the accuracy of 68% to 82%, as shown in Table 4. Using AR extraction reduced oscillation or instability of training as shown in Figure 6 and improved accuracy as shown Table 4.

Table 4 Accuracy of Classification System toward AR

Subject		Accuracy (%)		
		Grasping	Loosing	Relax
1	Without AR	72	66	73
	With AR	88	78	85
2	Without AR	73	62	71
	With AR	85	78	83
3	Without AR	70	67	69
	With AR	83	79	84
4	Without AR	68	61	66
	With AR	91	75	78
average	Without AR	71	64	70
	With AR	87	78	83

3.2.3 Performance of System Classification

In same situation the system was evaluated to four subjects each imagined three grasping states. The subjects that were used in the system testing are different with subjects that were used in training. The subjects were recorded 96 testing data. The result are shown as Table 5. Classification systems are designed using ANN with Adaptive Backpropagation algorithm in system learning that was compared to backpropagation algorithm ini same situation. We got accuracy improving of 76% to 82% comparing conventional Backpropagation as showed Table 5. Adaptive Backpropagation accelerated the training time up to 15 minutes by using 240 of training data. The result was average 87% of grasping, 78% of loosing, and 83% of relax imagination. It was 82% of all state.

Table 5 Accuracy between BP and Adaptive BP

Subject		Accuracy (%)		
		Grasping	Loosing	Relax
1	BP	77	72	76
	Adaptive BP	88	78	85
2	BP	78	78	77
	Adaptive BP	85	78	83
3	BP	74	70	78
	Adaptive BP	83	79	84
4	BP	80	77	72
	Adaptive BP	91	75	78
average	BP	77	74	76
	Adaptive BP	87	78	83

4.0 CONCLUSION

The research has shown proposed methods which using 20th Order Autoregressive extraction and neural networks with Adaptive Backpropagation algorithm can be to classify grasping imagination of EEG signals. It used 0.1 fixed earning rate, 50 hidden neurons, 0.09 tolerance of MSE. Using AR coefficients could increase accuracy of 68% to 82%. Besides, it reduced training time and oscillation.

Using Adaptive backpropagation could improve the accuracy of 76% to 82% toward 240 testing data. An EEG signal identification system for grasping imagination has been implemented in software that is integrated with wireless EEG, so it can be used for Brain Computer Interface.

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References

[1] Zhang, X. D., and Choi, H. R. 2006. Pattern Recognition of Human Grasping Operation Based on EEG. *International Journal of Control, Automation, and Systems.* 4(5): 592-600.

[2] Yulianto, E., Susanto, A., Widodo, T. S., Wibowo, S. 2012. Classifying the EEG Signal through Stimulus of Motor Movement Using New Type of Wavelet. *IAES International Journal of Artificial Intelligence.* 1(3): 139-148.

[3] Zabidi, W. Mansor, K. Y. Lee, C. W Fadzal. 2012. Classification Of EEG Signal from Imagined Writing Using A Combined Autoregressive Model And Multi-Layer Perceptron. *Conference.* 964-968.

[4] C. W. N. F. Fadzal, C. W., Mansor, W., Khuan, L. Y. 2011. An Analysis of EEG Signal Generated From Grasping and Writing, *International Conference on Computer Applications and Industrial Electronics* (ICCAIE 2011). 535-537.

[5] Erfanian, A. Erfani, 2004. ICA-based Classification Scheme for EEG-based Brain-computer Interface: The Role of Mental Practice and Concentration Skills. *Engineering in Medicine and Biology Society, 26th Annual International Conference of the IEEE*. 1: 235-238.

[6] Amanpour, A. Erfanian, 2013. Classification of Brain Signals Associated with Imagination of Hand Grasping, Opening and Reaching by Means of Wavelet-based Common Spatial Pattern and Mutual Information. *Engineering in Medicine and Biology Society* (EMBC) 2013. Osaka, Japan. 3-7 July 2013. 2224-2227.

[7] Zhang, X. D., Wang, Y. X., Li, Y. N., Zhang, J. J. 2011. An Approach for Pattern Recognition of EEG Applied in Prosthetic Hand Drive. *Systemics Cybernetics and Informatics*. 9(6): 51-56.

[8] Mosquera, C., Verleysen, M. and Vazquez, A. N. 2010. EEG Feature Selection Using Mutual Information and Support Vector Machine: A Comparative Analysis. *32nd Annual International Conference of the IEEE EMBS. Buenos Aires, Argentina*. 4946-4949.

[9] Turnip, A., and Hong, K. S. 2012. Classifiying Mental Activities from EEG - p300 Signal Using Adaptive Neural Networks. *International Journal of Innovative Computing*. September. 8(9): 6429-6443.

[10] Liu, N. H., Chiang, C. Y., and Chu, H. C. 2013. Recognizing the Degree of Human Attention Using EEG Signals from Mobile Sensors. *Sensors*. 10273-10286.

[11] Duan, R. N., Wang, X. W, and Lu, B. L. 2012. EEG-Based Emotion Recognition in Listening Music by Using Support Vector Machine and Linear Dynamic System. *ICONIP 2012*. Part IV. LNCS 7666. 468-475.

[12] Soleymani, M., Pantic, M., and Pun, T. 2012. Multimodal Emotion Recognition in Response to Videos. *IEEE Transactions on Affective Computing*. 3(2): 211-223.

[13] Bhardwaj, A. Gupta, P. Jain and Rani, A. 2015. Classification Of Human Emotions From EEG Signals Using SVM And LDA Classifiers. *2nd International Conference on Signal Processing and Integrated Networks (SPIN)*. 2015. Noida. 19-20 February. 180-185.

[14] Trejo, L. J., Knuth, K., Prado, R., Rosipal, R., Kubitz, K. 2007. EEG-Based Estimation of Mental Fatigue, Convergent Evidence for a Three-State Model. *Foundations of Augmented Cognition Lecture Notes in Computer Science*. 4565: 201-211.

[15] Djamal, E. C., Suprijanto, Arif, A. 2014. Identification of Alertness State Based on EEG Signal Using Wavelet Extraction and Neural Networks. *Proceedings of International Conference Computer, Control, Informatics and Its Applications* (IC3INA) 2014. 182-186.

[16] Kiymik, M. K., Akin, M., and Subasi, A. 2004. Automatic Recognition of Alertness Level by Using Wavelet Transform and Artificial Neural Network. *Journal of Neuroscience Methods. Elsevier*. 139: 231-240.

[17] Liang, S. F., Lin, C. T., Wu, R. C. Chen, Y.C., 2005. Monitoring Driver's Alertness Based on the Driving Performance Estimation and the EEG Power Spectrum Analysis. *Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*. Shanghai, China. September 2005. 1-4.

[18] Teplan, M., Krakovská, A., and Štolc, S. 2006. Short-term Effects of Audio-visual Stimulation on EEG, *Measurement Science Review*. 6(2).

[19] Djamal, E. C., and Suprijanto. 2011. Recognition of Electroencephalogram Signal Pattern against Sound Stimulation using Spectral of Wavelet. *Proceedings of TENCON 2011. Bali, Indonesia*. Nov 2011. 374-378.

[20] Djamal, E. C., and Tjokronegoro, H. A. 2005. Identification and Classification of EEG Signal toward Sound Stimulation Using Wavelet Extraction and Power Spectral. *Journal of Mathematical and Fundamental Sciences*. 37(1): 69-92.

[21] Palaniappan, R., Huan, N. J. 2005. Effects of Hidden Unit Sizes and Autoregressive Features in Mental Task Classification, *Proceedings of World Academy of Science, Engineering and Technology*. 7: 288-293.

[22] Steinberg, H. W., Gasser, T., Franke, J. 2003. Fitting Autoregressive Models to EEG Time Series: An empirical Comparison of Estimates of the Order. *Acoustics, Speech and Signal Processing, IEEE Transactions*. 33(1): 143-150.

[23] Mohammadi, G., Shoushtari, P., Ardekani, B. M., and Shamsollah, M. B. 2006. Person Identification by Using AR Model for EEG Signals. *Proceedings of World Academy of Science, Engineering and Technology 2006*. 11. February 2006. 281-285.

[24] Lin, Y. P, Wang, C. H, Wu, T. L., and Jeng, S. K. 2007. Multilayer Perceptron for EEG Signal Classification During Listening to Emotional Music. *TENCON 2007*. Taipei, Taiwan. 1-3.

[25] Subavathi, S. J., and Kathirvalavakumar, T. 2011. Adaptive Modified Backpropagation Algorithm Based on Differential Error. *International Journal of Computer Science, Engineering and Application* (IJCSEA). 1(5). October. 21-34.

[26] Boardman, A. Schlindwein, F. S. Rocha, A. P. Leit, A. 2002. A Study On The Optimum Order of Autoregressive Models for Heart Rate Variability. *Physiol. Meas.* 23: 325-336.