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ARTIFICIAL INTELLIGENCE

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Volume II

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SESSION: HEURISTIC SEARCH + INFORMATION RETRIEVAL + PATTERN AND SIMILARITY ANALYSIS

SESSION: ARTIFICIAL INTELLIGENCE, ALGORITHMS, NOVEL APPLICATIONS AND CONCEPTS

Head movement artifact removal in EEG signals using Empirical Mode Decomposition and Pearson Correlation

Gerardo Rosas-Cholula[1], Juan Manuel Ramirez-Cortes[1], Jose Rangel-Magdaleno[1], Pilar Gomez-Gil[2], Vicente Alarcon-Aquino[3]

[1]National Institute of Astrophysics, Optics and Electronics. Department of Electronics
Calle Luis Enrique Erro No. 1, Tonantzintla, Puebla, 72760, Mexico
[2]National Institute of Astrophysics, Optics and Electronics. Computer Science Department
Calle Luis Enrique Erro No. 1, Tonantzintla, Puebla, 72760, Mexico
[3]University of the Americas, Puebla. Department of Electronics and Computer Science
Exhda. Sta. Catarina Martir, Cholula, Puebla, 72720, Mexico

Abstract

This paper presents an approach on head movement artifact removal from EEG signals, in the context of an ongoing brain computer interface project. The proposed artifact removal scheme is based on Empirical Mode Decomposition (EMD) applied to the signals obtained from each electrode. Correlation analysis using Pearson coefficient allows identification of those intrinsic mode functions related to common artifacts, which are associated to head movement. The goal of this experiment is separation of signals corresponding to single and double blinking from head movement artifacts. Once the preprocessing is applied, blinking detection is reduced to threshold operations. Final selection step based on Mahalanobis distance provides a detection rate of 95% in average.

Keywords: EEG, artifact, empirical mode decomposition, correlation.

1. Introduction

Artifacts caused by movement of the head during the acquisition of EEG signals constitute a significant limitation in a number of applications, such as data clinical interpretations, automated systems for analysis or detection of pathologies, human-computer interfaces (HCI), and brain computer interface (BCI) applications. A BCI system aims to translate the electrical brain signals generated by a human being as a result of some thoughts, in commands able to perform some control actions in computerized mechanisms [1]. Affordable EEG devices recently released makes attractive the development of such systems, however, technical characteristics of those devices, such as poor signal to noise ratio, and some artifacts such as

electrode displacements, or subject movements require incorporation of additional signal processing techniques [2]. An important motivation to develop BCI systems is to allow an individual with severe motor disabilities to have control over specialized devices such as assistive appliances, neural prostheses, speech synthesizers, or a personal computer directly. Among a number of currently available technologies, EEG systems constitute a good alternative to develop BCI applications given some characteristics such as non-invasiveness, affordability, transportability, and size [3, 4]. However, EEG signals detected through surface electrodes present some problems, such as weak EEG electrical signals, low spatial resolution, artifact contamination, poor electrical contacts, and contact noise arising from head movements, manifested in EEG signals as additional artifacts. In practical situations of BCI systems, the user is expected to interact with automated equipment in a natural way, and head movements are part of that interaction. Additionally, because of the fluid, bone, and skin that separate the electrodes from the actual brain activity, the already small signals are scattered and attenuated before reaching the electrodes, with the consequence that head movement artifacts can reach amplitudes in the same order of magnitude of EEG signals related to brain activity, or even more. There have been several approaches oriented to do artifact removal in EEG signals with techniques such as independent component analysis (ICA) [6, 7, 8], high-order statistics and ICA [9], wavelet transform [10], adaptive least mean square [11], canonical correlation analysis [12], and others. Most reported papers consider muscle activity and blinking as EEG artifacts, although some works concentrate in removing only artifacts associated to EMG signals. The work presented in this paper is part of a project about the use of the EEG Emotiv® headset [13] as cursor control emulating the typical operations of a computer-mouse.

Computer mouse emulation using hands-free alternatives is a project which has been broadly pursued in the last decades. The following is a partial list of some successful modalities which have been reported: visual tracking [14], voice control [15], electromyographic signals [16], electro-oculographic potentials [17], and electroencephalographic signals [18, 19]. In this application, the Emotiv headset is used to indirectly detect EMG blinking signals reflected in the EEG activity captured through the headset. Blinking is used as a mean to perform the clicks required in a computer mouse. Although Emotiv EPOC headset represents an efficient alternative that is practical and economical, the EEG detected signals are noisy and contaminated with artifacts arising from different sources. Head movements associated to the expected use of the device as a mouse pointer will produce noise on the signal acquired by the electrode due to slight movements of the electrodes over the scalp. Cursor position is controlled using information from a gyroscope included in the headset, and clicks are generated through the user's blinking with a detection procedure based on Empirical Mode Decomposition (EMD), which is used to separate desired blinking signals from head movement artifacts. The rest of the paper is organized as follows: Section 2 describes principles associated to EMD. Section 3 presents the proposed scheme and a description of the included modules. Section 4 describes the experimental setup and the experiments carried out. Section 5 presents and discusses the obtained results, and section 6 presents some concluding remarks and future work of this research.

2. Empirical Mode Decomposition (EMD)

EMD was first introduced by Huang [20] for spectral analysis of non-linear and non-stationary time series, as the first step of a two stage process, currently known as the Hilbert Huang Transform (HHT). EMD is used in this work with two objectives: signal preprocessing to reduce noise arising from head movement, and double blinking detection to simulate the "click" operation of a traditional mouse device. Essentially, EMD aims to empirically identify the intrinsic oscillatory modes or intrinsic mode functions (IMF) of a signal by its characteristic time scales, in adaptive way. These modes represent the data by means of local zero mean oscillating waves obtained by a sifting process. Thus, an IMF satisfies two main conditions: taking account the complete data set, the number of extrema points (min and max) must be equal or differ at most by one to the number of zero crossing points; the mean value of the envelopes is always zero which are defined by the local maxima and local minima. EMD can be summarized as follows [21]: Given a signal $x(t)$ identify its extrema (both minima and maxima). Generate the envelope by connecting maxima and minima points with a curve, for instance, cubic spline interpolation, although other interpolation techniques are allowed. Determine the mean by averaging and extract

the detail, as expressed in eq. 1 and 2. Finally iterate on the residual $m(t)$.

$$m(t) = \frac{e_{min}(t) + e_{max}(t)}{2} \tag{1}$$
$$d(t) = x(t) - m(t) \tag{2}$$

There are some iteration stopping criterions such as establishing a certain number of siftings, a predefined threshold, or specifying a minimum amplitude of residual. EMD satisfies completeness and orthogonality properties in the same way as spectral decompositions, such as Fourier or wavelet transform. The completeness property is satisfied by EMD, meaning that it is possible to reconstruct the original signal based on their decompositions. These decomposition functions should all be locally orthogonal to each other, as expressed in equation 3, although some leakage may arise.

$$\overline{(x(t) - \overline{x(t)}) \cdot \overline{x(t)}} = 0 \tag{3}$$

An orthogonality index expressed in equation 4 is used to keep track of leakage magnitude within some limits. X is the original signal with $i \neq j$.

$$I_O = \sum_{t=0}^{T} \left(\frac{\sum_{j=1}^{n+1} \sum_{k=1}^{n+1} IMF_j(t) IMF_k(t)}{X^2(t)} \right) \tag{4}$$

Occasionally it is necessary to consider a local EMD. In this case, sifting operations are not applied to the full length signal. Sometimes there exist zones resulting in over-iteration to achieve a better local approximation contaminating other parts of signal and in consequence over-decomposing. Thus, the local zones where the error remains large have to be isolated, and the algorithm should maintain iterating only over these zones. Local EMD is implemented introducing a weighting function; this function must describe a soft decay outside the problem zone. In consequence equation 2 can be written as:

$$d(t) = x(t) - w(t)m(t) \tag{5}$$

Figure 1 shows typical results obtained from an EEG signal using EMD with five decomposition iterations.

3. Proposed scheme and module description

A BCI based on EEG analyzes ongoing electric brain activity for brain patterns that originate from specific brain areas. To get consistent recordings from specific regions of the head, scientists rely on a standard system for accurately

placing electrodes, which is called the International 10–20 System , generally used in clinical EEG recording and EEG research.
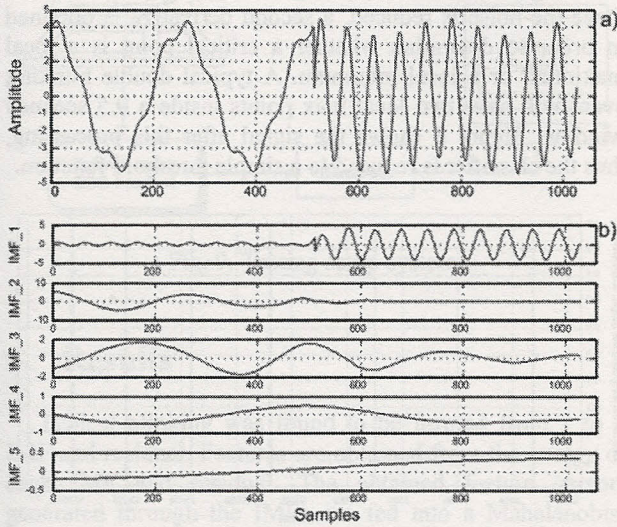

Fig. 1. EEG signal decomposition with the first five IMFs.

Figure 2 shows the electrode positions and denominations used in the international 10-20 system. The squares indicate the available electrodes on Emotiv system. The EEG signals required to perform the detection are obtained from electrodes AF3/AF4, which are labeled according to the mentioned 10-20 international system.
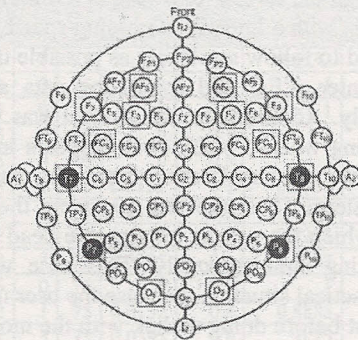

Fig. 2. International system 10-20.

The modules proposed to simultaneously separate head movement artifacts and blinking from the EEG signals are shown in the block diagram of figure 3. The artifact could be detected considering that noise present in all electrodes over the scalp will show high correlation. Thus, the proposed system is based on finding common signals in the electrodes, empirical mode decomposition, Pearson correlation, and an integration module which includes computation of Mahalanobis distance and further thresholding. Figure 4 shows an example of double blinking events immerse in noise produced by head movement.
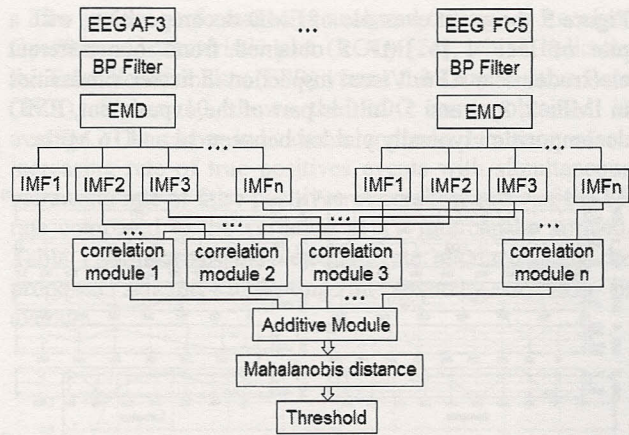

Fig. 3. Proposed scheme; head movement artifact and blinking detection

As previously stated, noise produced by head or body movement will appear in all electrodes of the system with small variations, therefore, correlation analysis using Pearson coefficient is used for noise detection purposes.
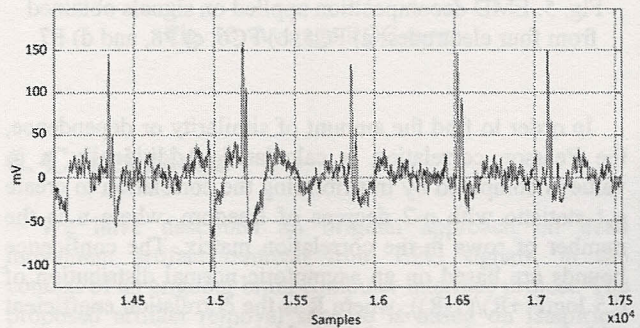

Fig. 4. Head movement noise during double blinking events.

Pearson correlation coefficient provides a measure of dependence between two random variables [22]. Equation 6 defines the Pearson correlation with expected values μ_X and μ_Y and standard deviations σ_X and σ_Y.

$$\rho_{X,Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \tag{6}$$

Correlation function applied directly to the signals obtained from each electrode will state dependence between channels. Common signals detected would have to be removed; however, applying directly an operation to separate those signals could cause removing also important information. Therefore, decomposing the signal from each electrode will reduce the loss of information, allowing the system to distinguish between artifacts from head movements and double blinking signals. That decomposition has been carried out using EMD technique.

Figure 5 shows an example of EMD decomposition, with a plot of IMF 1 to IMF 5 obtained from four different electrodes near AF6. Visual inspection indicates similarities in IMFs 1, 3, 4 and 5. In this part of the experiment, EMD decomposition typically yielded between 14 and 16 MFIs.
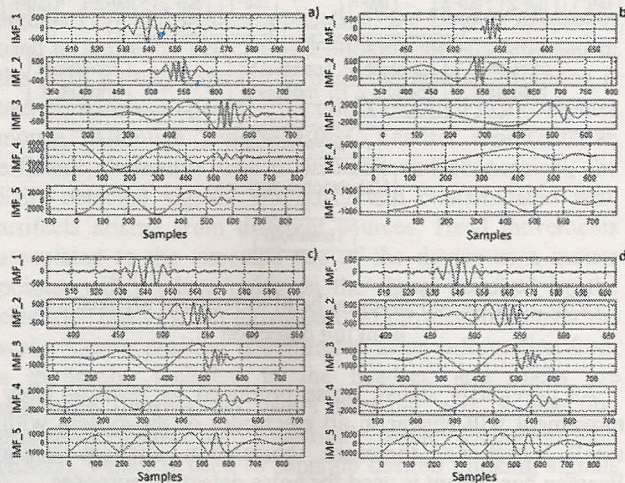

Fig. 5. EMD decomposition applied on signals obtained from four electrodes: a) FC5, b) FC6, c) P8, and d) P7.

In order to find the amount of similarity or dependence, the Pearson correlation is calculated. Additionally, a p-value is computed by transforming the correlation to create a t statistic with n-2 degrees of freedom, where n is the number of rows in the correlation matrix. The confidence bounds are based on an asymptotic normal distribution of $0.5 \log((1+R)/(1-R))$, where R is the correlation coefficient with an approximate variance of $1/(n-3)$.
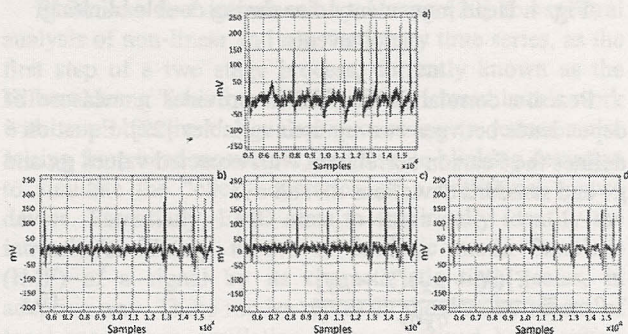

Fig. 6. Noise reduction based on correlation function removing a) 1 IMF, b) 2 IMFs, c) 3 IMFs and d) 4 IMFs.

This algorithm is repeated for all IMFs, taking as reference the electrode AF6. A slide window of 10 seconds is applied during correlation calculation. Figure 7 shows the noise reduction using the correlation coefficients associated to the Thus, p values less than 0.05 were considered to imply high correlation. Figure 17 shows an example in which IMF3 from electrode AF6 is compared to the rest, from a total

number of 12 electrodes, resulting in p-values close to 0, except for one electrode. corresponding IMF. If there is a correlation in most of the electrodes, the corresponding IMF is prevented from passing to the integration module. Once the noise is reduced, a second derivative is obtained in order to determine whether a critical point is a local maximum or a local minimum. A typical double blinking event will have two local max points inside a 0.5 seconds window. Figure 8 shows the signal after this processing, thus the classifier is reduced to a simple threshold function.
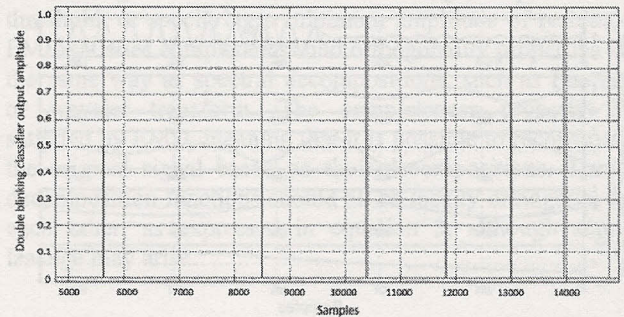

Fig. 7. Double blinking detection with noise reduction.

4. Experimental setup

Subjects under testing were seated in a comfortable position using the Emotiv headset with a laser pointer attached at the top, as shown in figure 8. A simple application developed in visual basic, showed a red circle moving through the screen following horizontal and vertical displacements, with a linearly increasing speed. The subject was instructed to follow as closely as possible the red circle with the pointer. EEG and gyroscope data are recorded simultaneously. Additionally, the subject was told to do a double blinking when a black circle appears in the screen. In that instant, the application sends a marker to the recording system. Thus, the test considers the worst case scenario in which the user is moving the head and doing a double blinking simultaneously. This case would rather occur in a practical situation, because the user usually stops the movement before doing a click with the mouse. Testing setup system is depicted in figure 15. Head movements during this action generates artifacts which have to be removed in order to distinguish user´s blinking.
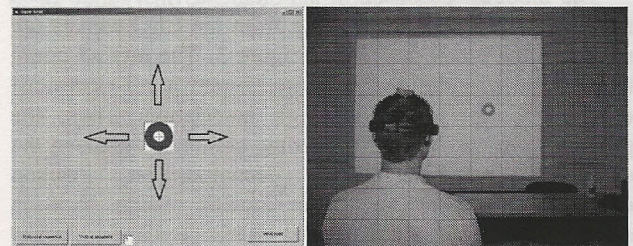

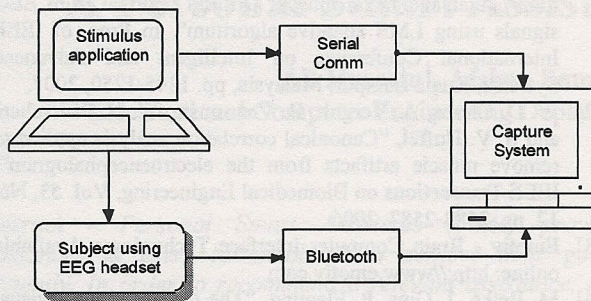Fig. 8. Experimental setup of EEG-based mouse emulation.

Fig. 9. Testing setup system.

5. Results

Typical blinking was found to be formed from 1 to 5 IMF and residual. Features are obtained from the energy of each IMF and residual. The obtained feature vectors generated through the IMFs are fed into a Mahalanobis-distance based classifier [23]. System test was performed using fold validation, dividing the data set in training and testing groups of 10 vectors each group, and finally the system is tested using 5 complete sequence of 91 seconds in which 10 double blinking events occur randomly. A double blinking event is experimentally found to fall inside a Mahalanobis distance value between -1.34 and -3.25.

The system performance is analyzed through a Receiver Operation Characteristic plot (ROC) [24], which indicates the False Positive Rate (FPR) versus the True Positive Rate (TPR). Figure 10 shows the ROC curve obtained in average. The curve indicates a common tendency of an increasing rate of true positives events with simultaneous increasing rate of false positives. A small increase of the FP rate compared to the variation of TP rate can be noticed. Table I summarizes the detection rate obtained using the proposed scheme, indicating an accuracy of 95% in average.
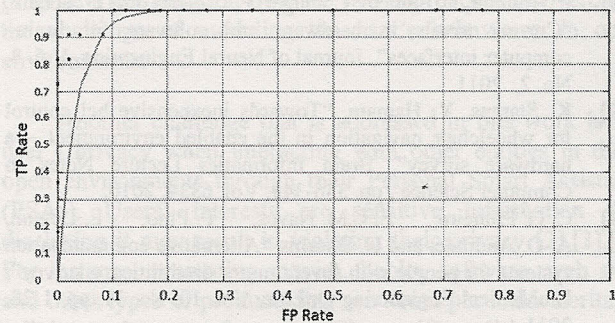

Fig. 10. Average ROC curve.

Table I. Average detection rate and performance metrics.

TP	FN	FP	TN	FP Rate	TP Rate	Precision	Accuracy
5	5	1	75	0.0132	0.5	0.8333	0.9302
8	2	0	76	0	0.8	1	0.9767
5	5	0	76	0	0.5	1	0.9418
5	5	0	76	0	0.5	1	0.9418
5	5	0	76	0	0.5	1	0.9418
7	3	1	75	0.0132	0.7	0.8751	0.9534
9	1	1	75	0.0132	0.9	0.9	0.9767
8	2	3	73	0.0395	0.8	0.7272	0.9418
8	2	3	73	0.0395	0.8	0.7272	0.9418
5	5	0	76	0	0.5	1	0.9418
8	2	1	75	0.0132	0.8	0.8888	0.9651
9	1	3	73	0.0395	0.9	0.75	0.9534
5	5	0	76	0	0.5	1	0.9418
5	5	0	76	0	0.5	1	0.9418
5	5	0	76	0	0.5	1	0.9418
10	0	4	72	0.0526	1	0.7142	0.9534
6	4	0	76	0	0.6	1	0.9534
9	1	2	74	0.0263	0.9	0.8181	0.9651
5	5	0	76	0	0.5	1	0.9418
5	5	0	76	0	0.5	1	0.9418
3	7	0	76	0	0.3	1	0.9186
5	5	0	76	0	0.5	1	0.9418
5	5	0	76	0	0.5	1	0.9418
10	0	2	74	0.0263	1	0.8333	0.9767
9	1	1	75	0.0132	0.9	0.9	0.9767

6. Conclusions

We have described an original approach on head movement artifact removal from EEG signals, in the context of an ongoing brain computer interface project. The proposed artifact removal scheme is based on Empirical Mode Decomposition (EMD) applied to the signals obtained from each electrode. Correlation analysis using Pearson coefficient allowed identification of those intrinsic mode functions related to common artifacts, which are associated to head movement. System performance showed very good results on separation of blinking from head movement artifacts. The proposed signal processing system was applied to emulation of clicks in a computer mouse. Final selection step based on Mahalanobis distance provided a detection rate of 95% in average. Analysis on detection rate indicated that EMD provided an efficient, effective and quick computational tool, adequate to non-stationary signals. The proposed noise reduction method based on information available from multiple electrodes is a preprocessing technique which can be adapted to different EEG systems, when noise caused by head or body movement is required to be removed. Additional experiments exploring the incorporation of classifiers such as Support Vector Machine and Neural Networks are currently in progress.

7. Acknowledgments

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ICAI'13 & GEM'13 CONFERENCE SCHEDULES

The 2013 International Conference on Artificial Intelligence (ICAI'13)
+
The 2013 International Conference on Genetic and Evolutionary Methods (GEM'13)

SESSION 3-ICAI: (CONCURRENT SESSION WITH SESSION 4-GEM)
NATURAL LANGUAGE PROCESSING AND RELATED METHODS
Co-Chairs: Dr. Nayat Sanchez-Pi, ADDLabs, Universidade Federal
Fluminense. Brazil;
Dr. Steve Richfield, CTO of our thing, Washington, USA
July 23, 2013 (Tuesday); 08:00am - 10:20am
(LOCATION: Cohiba 7)

08:00 - 08:20am: A Knowledge-Based Approach to Word Sense Disambiguation
Waleed Faris and Kam-Hoi Cheng
University of Houston, Houston, Texas, USA

08:20 - 08:40am: Computer-based Method for Association Response in Autonomous Conversation
Eriko Yoshimura, Misako Imono, Seiji Tsuchiya, Hirokazu Watabe
Doshisha University, Japan

08:40 - 09:00am: Method to Add New Attributes to Concepts by Web and Second-order
Attributes
Misako Imono, Eriko Yoshimura, Seiji Tsuchiya, Hirokazu Watabe
Doshisha University, Japan

09:00 - 09:20am: Development Of Filipino Phonetically-Balanced Words And Test Using
Hidden Markov Model
Arnel C. Fajardo and Yoon-joong Kim
Hanbat National University, Daejon, South Korea

09:20 - 09:40am: How to Make NL "Understanding" Systems Run Orders of Magnitude Faster
Steve Richfield
CTO of our thing, Edgewood, Washington, USA

09:40 - 10:00am: Meaning Judgment Method for Alphabet Abbreviation Using Wikipedia and
Earth Mover's Distance
Seiji Tsuchiya, Misako Imono, Eriko Yoshimura, Hirokazu Watabe
Doshisha University, Japan

10:00 - 10:20am: Implementation of Intelligence Robotic Engines Using Ontologies and
Process Natural Language
Rafael Luiz de Macedo, Elvis Fusco, Fabio Dacencio Pereira
University Center Euripides of Marilia, Brazil

O. Application of Fuzzy System for Analysis of Lightning Overvoltages and Protection of Distribution Systems by Surge Arresters
M. A. Araujo, R. A. Flauzino, O. E. Batista, L. A. Moraes
University of Sao Paulo (USP), Sao Carlos, Brazil

O. Efficient Integration of Intelligent Systems and Experimental Tests for Power Transmission Transformer Diagnosis
C.G. Gonzales, M.A. Carrapato, T.S. Bonfin, P.I. Costa, D.H. Spatti, R.A. Flauzino, and I.N. Silva
Sao Paulo Power Transmission Company, Companhia de Transmissao de Energia
Eletrica Paulista, Brazil; University of Sao Paulo, Brazil

O. ...

SESSION 5-ICAI: **(CONCURRENT SESSION WITH SESSION 6-ICAI)**
ARTIFICIAL INTELLIGENCE, ALGORITHMS, NOVEL APPLICATIONS & CONCEPTS
Co-Chairs: Dr. Curry Guinn, University of North Carolina Wilmington, USA;
Ms. Mota-Valtierra Georgina, Universidad Autonoma de Queretaro, Mexico
July 23, 2013 (Tuesday); 11:00am - 06:00pm
(LOCATION: Cohiba 7)

11:00 - 11:20am: Crowd Evacuation Control for Public Spaces
Pejman Kamkarian and Henry Hexmoor
Southern Illinois University, Carbondale, Illinois, USA

11:20 - 11:40am: Head Movement Artifact Removal in EEG Signals Using Empirical Mode Decomposition and Pearson Correlation
Gerardo Rosas-Cholula, Juan Manuel Ramirez-Cortes, Jose Rangel-Magdaleno, Pilar Gomez-Gil, and Vicente Alarcon-Aquino
National Institute of Astrophysics, Optics and Electronics, Mexico; University of the Americas, Puebla, Mexico

11:40 - 12:00pm: A Personal Smart Assistant For Open Environments
Ali Hussain, Afshan Samani, Hamada H. Ghenniwa
Western University, London, Canada

12:00 - 12:20pm: Simultaneous Events Handling
Nathaniel Nana Kojo Taylor
Bowie State University, Bowie, USA

12:20 - 01:20pm: LUNCH (On Your Own)

01:20 - 01:40pm: Forgetting Classification and Measurement for Decomposition-based Reinforcement Learning
Sean Mondesire and R. Paul Wiegand
University of Central Florida, Orlando, Florida, USA

01:40 - 02:00pm: An Extraction of Influential Lightings for Illuminance Sensors and Lighting Off Mechanism in An Intelligent Lighting System
Mitsunori Miki, Yohei Azuma, Hisanori Ikegami
Doshisha University, Japan

02:00 - 02:20pm: Computational Methods for Determining the Similarity Between Ancient Greek Manuscripts
Eddie Dunn, Curry Guinn, George Zervos
University of North Carolina Wilmington, North Carolina, USA

02:20 - 02:40pm: Self-Adaptive Feature Selection Strategy for Multi-types Object Classification Problem
Namdar Mogharreban and Tianyang Wang
Southern Illinois University, Carbondale, Illinois, USA