Autoregressive Modeling of Visual Evoked Potentials and Its Applications to Optic Nerve Diseases-Ischemic Optic Neuropathy and Optic Neuritis

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***Abstract*—** It is important to differentiate the diagnosis of ischemic optic neuropathy (ION) and optic neuritis (ON) for prognostic and therapeutic reasons. In most cases, differentiation is accomplished by assessing the disc appearance, the presence or absence of retrobulbar pain, the age of the patient, the mode of onset and other features of clinical and laboratory evaluation. However, in certain groups of patients, diagnosis may be difficult because of overlapping clinical profiles in these two disorders. In this paper, an attempt is made to overcome clinically overlapping profiles and to evolve indices to classify and delineate clearly ION and ON groups by differential diagnosis of the visual evoked potentials (VEP) using autoregressive (AR) modeling. In the present work of AR modeling, the data sequence x(n) as the output of a linear system has been carried out using digitized VEP waveform. An appropriate optimal order p for the AR model is chosen based on the Akaike information criterion (AIC). Accordingly, AR model has eight coefficients for each data sequence. These AR model coefficients are computed using Burg's algorithm. These AR coefficients with different combinations were plotted in the feature plane representations, for distinction between the ION and ON group of patients. It was found that, the feature plane plot of a_2 verses a_7 has a potential to distinguish clearly the ION and ON patients with respect to normal subjects. This novel technique using the AR feature plane representation is more efficient and thus, enables the neurologist in early therapy planning.

Keywords- *Visual evoked potential; Ischemic optic neuropathy; Optic neuritis; AR modeling; Feature plane representation; Akaike information criterion*

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I. INTRODUCTION

The brain works through complex electrical and chemical processes. Brain is formed of two cerebral hemispheres- right and left. Each cerebral hemisphere is formed of four lobes. Frontal lobe (motor area), Parietal lobe (sensory area), Temporal lobe (hearing & memory) and Occipital lobe (Vision) [1]. Evoked Potentials (EPs) are bioelectric signals generated by the central nervous system (CNS) when it is stimulated by well defined external events. EPs have been studied in patients with neurological diseases since the early 1950s, but it was only in the early 1970s that EPs began to have definite clinical utility. The most commonly used clinical EPs are the checkerboard visual EPs (VEPs), the brain-stem auditory EPs (BAEPs) and somatosensory EPs (SEPs). These are now routinely available in most hospitals and many neurological practice settings. VEPs have been known since the 1960s and have been used as a functional indicator in the diagnosis of the visual system.

VEPs are electric potential differences recorded from scalp in response to visual stimuli. These potentials are generated in the posterior part of the occipital lobe as shown in Figure1. Normal cortical responses are obtained if the entire visual system is intact and disturbance anywhere in the visual system can produce abnormal VEPs.

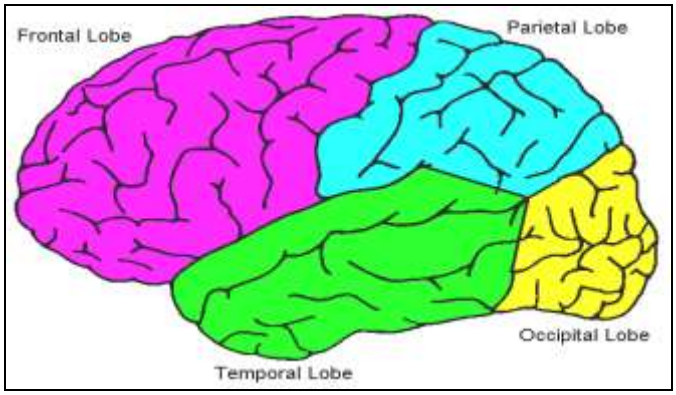

Figure1. Lobes of the human brain

Reduced amplitude and prolonged latencies in comparison with those of healthy controls are reliable indicators for pathological changes in visual pathways [2]. VEPs can detect functional loss in the visual pathway from retina to the visual cortex. The amplitudes and latencies of VEPs are affected considerably by the diseases of the visual pathways. ION leading to axonal loss produces normal P100 latency and decreased amplitude. Optic neuropathy (ON) is a disease

which affects the optic nerve severely. If not diagnosed and treated at an early stage it results in blindness. Differential diagnosis of ION and ON is important for prognostic and therapeutic reasons. In clinical practice, diagnosis is accomplished by the analysis of signs and symptoms, and other features of clinical and laboratory evaluation. However, signs and symptoms of these two disorders overlap in certain group of patients, making differential diagnosis difficult for the neurologist. This study aims to differentiate ION and ON groups with respect to normal group using AR modeling. Section II focuses on the methodology employed in this work. Results and discussion are narrated in section III while the conclusions are consolidated in section IV.

II METHODOLOGY

Detailed methodology employed in this work is described in the sub-sections to follow:

A. Materials and Methods

Recording of VEPs is done routinely in clinical practice by using a typical electro-diagnostic test setup. The eyes of the subjects are tested one at a time while the other eye is covered with an eye patch. Standard nomenclature has been adopted for describing the VEP waveform. The usual convention is that upward deviation caused by an impulse relative to reference is defined as negative. Waveforms of VEP are named by their polarity (P or N) followed by their latency (often indicated by a bar over the number). Latency is defined as the time interval between the onset of a controlled stimulus and a selected peak in VEP signal. Important features of the VEP, namely, latency and amplitudes are measured because of their significant relevance in electro-physiological diagnosis in neurology and neuro-ophthalmology. In clinical practice, the amplitude between the first positive peak P100 and the preceding negative trough N75 and the peak latency of the P100 component are measured.

B. Subjects

Study group consisted of 34 normal subjects with ages ranging from 20 to 60 years (mean 39 years) and patients group of 83 subjects. Amongst the patients group, ON was diagnosed in 63 subjects ranging from 20 to 60 years (mean 41 years) and ION was diagnosed in the rest of the patients group with ages ranging from 20 to 60 years (mean 48 years).

For the best results of VEP testing, the patient was explained about the test to ensure full cooperation and advised to avoid hair spray or oil after the last hair wash. Further, any meiotic or mydriatic drugs 12 hours before the test must be avoided. The usual glasses if any should be put on during the test [3, 4].

C. Electrodes and Electrode Placement

Standard silver-silver-chloride, disc type surface electrodes of 10 mm diameter, 1.5 m lead lengths were employed for recording VEPs. The electrode site was prepared by rubbing with a cotton swab dipped in an Abrasive Skin Prepping Gel (Nuprep^{TM}). The electrodes were filled with Ten20^{TM} conductive EEG paste and held in place on the scalp using 3M micro pore adhesive tape. The electrode impedance was less than 5 kΩ. Electrodes were placed relative to bony skull landmarks, in proportion to the size of the head, according to the International 10/20 system of EEG electrode placement configuration. Figure 2 depicts the nomenclature adopted for electrodes while recording VEP. Accordingly, the ground electrode is placed on the forehead (F_{pz}). The measuring and reference electrodes are placed on the scalp over the visual cortex (O_z) and on the vertex (C_z), respectively [5].

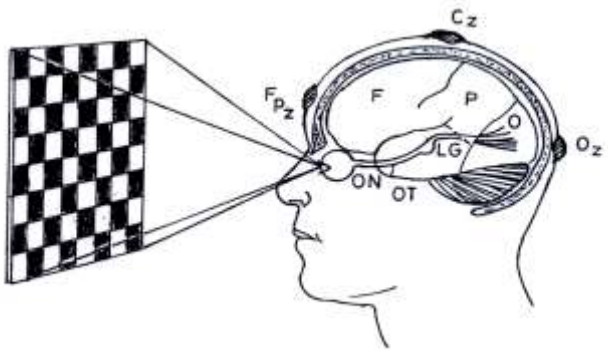

Figure 2. Schematic of VEP Recording

D. Signal acquisition

All VEP recordings were performed in a dark and sound attenuated room in the neuro-diagnostic laboratory of Vijay Health Centre, Chennai. Subject was asked to sit comfortably in front of the checkerboard pattern at an eye-screen distance of 100 cm. The stimulus pattern was a black and white checkerboard displayed on a Sanyo B/W video monitor, with individual checks subtending 2.29˚ and the entire pattern 18.32˚ at the eyes of the subject. The checks alternate from black/white to white/black at a rate of approximately twice per second [6]. The subject was instructed to gaze at a colored dot on the centre of the monitor screen. Every time the pattern alternates, the patient's visual system generates an electrical response and was recorded using electrodes. Signal acquisition and stimulus presentation was controlled by Cadwell Sierra - II Electro - diagnostic test setup, with filter settings at 1-100 Hz. The starting point of VEP waveform is stimulus onset. The VEP waveform recording is done over a period of 250 ms. More than 100 epochs were averaged to ensure a clear VEP waveform. For judging the reproducibility, the waveform is recorded twice and superimposed. A typical averaged VEP waveform is shown in Figure 3.

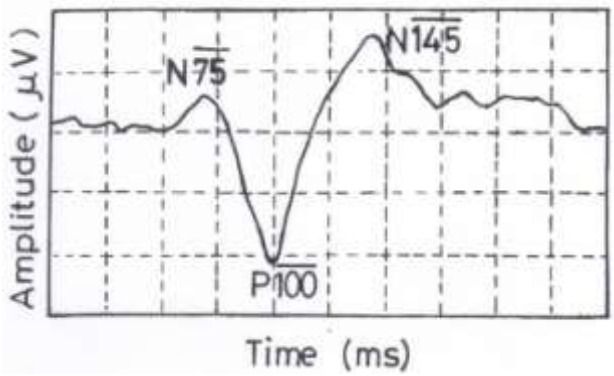

Figure 3. Typical VEP waveform

E. Parametric Model

The VEP waveform recording is carried out for 250 ms. Every recorded VEP waveform is digitized using Grafula

software with an inter-sample interval of 0.66 ms, thus providing 375 digital data sequence. Amongst the three parametric models namely an autoregressive moving average (ARMA) process of order (p,q), a moving average (MA) process of order q, and an autoregressive (AR) process of order p, an AR model is the most widely used. AR model is suitable for representing spectra with narrow peaks and also it results in very simple linear equations for the AR parameters, hence adopted in the present work [7].

In the AR model (also called linear prediction model), each sample x(n) of the VEP is described as a linear combination of previous samples plus an error term e(n) which is independent of past samples and is given by the following equation.

$$x(n) = -\sum_{k=1}^{p} a_k\, x(n-k) + e(n) \quad \text{---------- (1)}$$

where
x(n) : samples of modeled signal (VEP data sequence)
a_k : AR coefficients
p : order of the model
e(n) : residual or error in sequence

The model can be interpreted as a linear system with e(n) as its input and x(n) its output. The transfer function H(Z) of the model that represents an AR filter is given as

$$H(Z) = \frac{X(Z)}{Y(Z)} = \frac{1}{1+\sum_{k=1}^{p} a_k z^{-k}} \quad \text{---------- (2)}$$

H(Z) contains poles only [8].

The AR model can be constructed using one of several algorithms to compute model coefficients. They include the least-squares approach, which minimizes the prediction error in the least squares sense (either forward prediction or both forward and backward prediction errors), the Burg lattice method, which solves the lattice filter equations using the mean (either harmonic or geometric) of forward and backward squared prediction errors used, and the Yule-Walker method , which solves the Yule-Walker equations formed from sample covariances, minimizing the forward prediction error [9]. Out of these three methods, the Burg method is found to be the best because it results in high frequency resolution, yields a stable AR model and it is computationally efficient. One issue that is of critical importance in the successful application of AR modeling is the selection of the model order. There have been many criteria formulated over the years for determining the optimal model order. The most well known of these is Akaike's Information Criterion [10].

The complexity of the AR process is usually referred to as the order p of the AR model, which normalizes the prediction error of the coefficient estimation procedure [11]. To estimate the model order for VEP data sequence, the Akaike information criterion (AIC) has been used, which is based on the maximum likelihood analysis. This criterion is given by

$$AIC(p) = \ln(\sigma^2) + 2p/N \quad \text{---------- (3)}$$

where p is the order of the model, N is the number of data points, and σ^2 is the error variance for model order p.

As the order of the AR model is increased, the term σ^2 decreases and hence $\ln(\sigma^2)$ also decreases. However, 2p/N increases with an increase in p. Therefore, a minimum value is obtained for some p. Hence, this function is evaluated for a number of p values and the optimum p is the one that minimizes AIC(p). The value of AIC(p) is estimated for order (p) ranging from 2 to 24 and plotted as shown in Figure 4, which depicts the test for optimal AR model order.

From Figure 4 it is clear that, corresponding to the minimum value of AIC (p) the model order is eight.

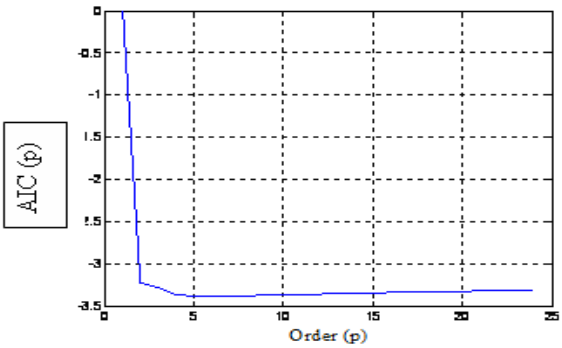

Figure 4. Akaike information criteria

The coefficients obtained from the model are: a_1, a_2, a_3, a_4, a_5, a_6, a_7, and a_8. These AR coefficients were computed using Burg's algorithm in MATLAB.

III RESULTS AND DISCUSSION

In this study, the AR coefficients are plotted in the feature plane representation for a clear distinction between ION and ON patient groups with respect to normal subjects. The different feature plane representations are a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8 versus one of these coefficients chosen as reference axis each time. Figures 5 (a – g) indicate typical feature plane plots of AR coefficients, where a_1, a_2, a_3, a_4, a_5, a_7, a_8 versus a_6 is considered. For all the ION patients it is observed from the Figures 5 (a – g) that, the a_6 coefficient is negative. The coefficients a_4, a_5, a_8 are positive but a_1, a_2, a_3, a_7 are negative.

In case of ON group of patients a_6 coefficient is positive in all the above cases, the coefficients a_1, a_4, a_5 are positive and a_2, a_3, a_7, a_8 are negative. For normal subjects a_6 coefficient is positive in all the cases. The coefficients a_1, a_2, a_3, a_7, a_8 are negative while a_4, a_5 are positive. It is not uncommon, to get similar kind of observations even after plotting different coefficients taking one coefficient as a reference each time. These types of variations in the coefficient will not yield any kind of relationship existing between ION and ON group of patients with respect to normal subjects.

However, it is interesting to observe from Figure 6, monotonically decreasing trend of these coefficients values between ION and ON group of patients with respect to normal subjects which follows a definite pattern. This kind of linear relationship is of particular significance of the variation in AR coefficients without any overlap of these groups Viz., ION, ON and normal, which makes the interpretation more convenient and easy.

This may become feature vector and hence it is preferred. Therefore, amongst the different feature plane plots discussed herein, Figure 6 is preferred primarily for extracting the progressive features of VEP signals necessary for clinical evaluation and secondarily to classify the subjects into different classes. This novel technique using the AR feature plane representation is applicable to differentiate clearly the VEP signals into ION and ON with respect to normal subjects. The present analysis requires only the recording of VEP signals of the affected eye, while traditional classification in routine clinical practice requires the recording of the both affected as well as unaffected eyes of a patient.

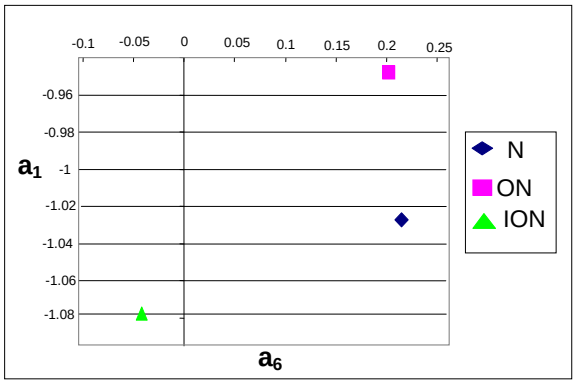

Figure 5(a). Plot of a_1 Vs a_6 Coefficient

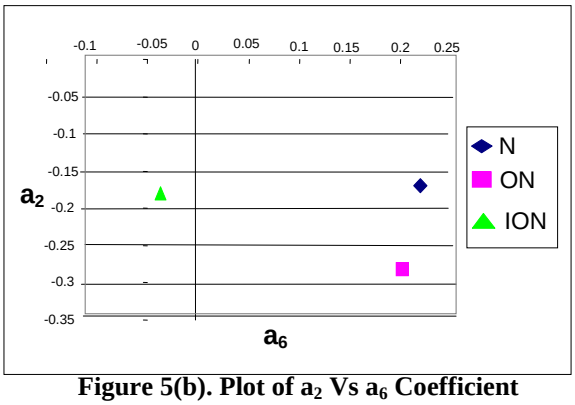

Figure 5(b). Plot of a_2 Vs a_6 Coefficient

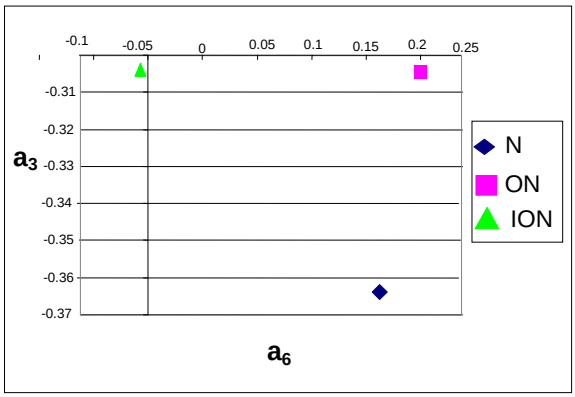

Figure 5(c). a_3 Vs a_6 Coefficient

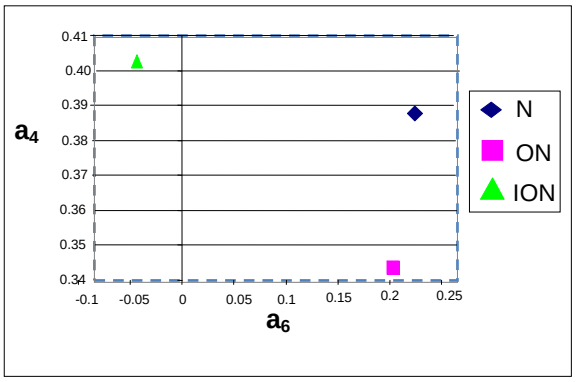

Figure 5(d). a_4 Vs a_6 Coefficient

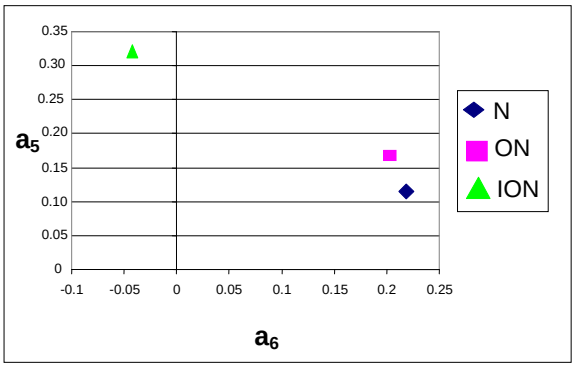

Figure 5(e). a_5 Vs a_6 Coefficient

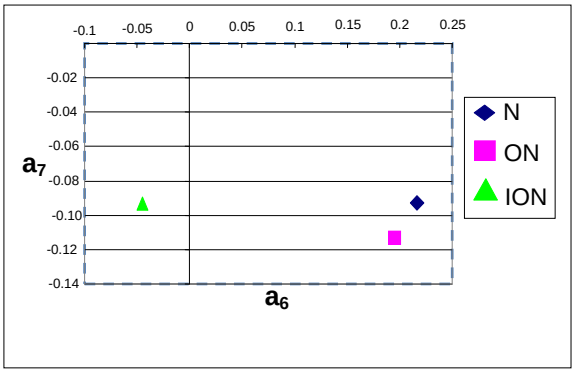

Figure 5(f). a_7 Vs a_6 Coefficient

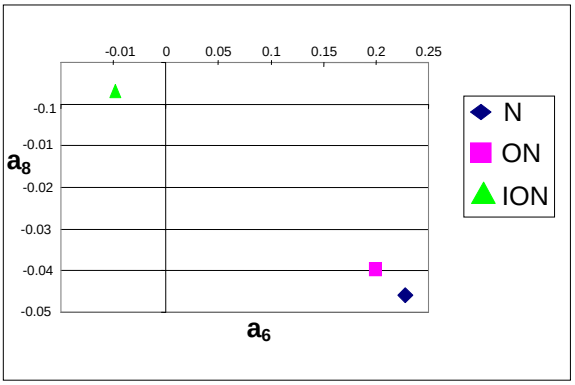

Figure 5(g). a_8 Vs a_6 Coefficient

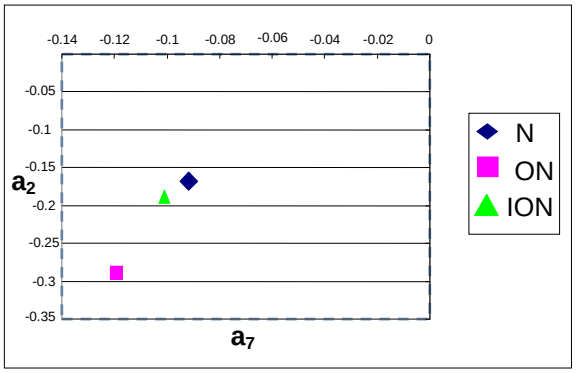

Figure 6. a_2 Vs a_7 Coefficient

IV CONCLUSION

Traditional VEP analysis is primarily concerned with P100 latency. AR modeling is employed to provide information on the overall composition of the waveform that is not disclosed by P100 peak latency measurements. Investigation of VEP by AR modeling is an attractive analytic approach because it allows detection of subtle waveform abnormalities that may escape detection with normal latency measurements.

Visual interpretation is subjective, depends more on personal skills and hence does not lend itself to statistical analysis. Consequently, quantitative VEP analysis methods based on advanced digital signal processing techniques would be of great value for neurologists in deciding therapy.

The VEPs were recorded over a number of normal subjects and patients have been classified using AR modeling. The AR coefficients were estimated from Burg's algorithm. These AR coefficients were plotted onto the feature plane representation and they resulted for a clear distinction between the ION and ON patient with respect to normal subject. Amongst the different feature plane plots, the plot of a_2 versus a_7 is the most preferred. This novel technique using the AR feature plane representation is handy to differentiate clearly the VEP signals into ION and ON patient groups with respect to normal subjects. Suffice it to conclude that the AR modeling technique is undoubtedly more reliable than conventional methods in vogue, thus helps neurologists in diagnostic and prognostic approach.

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V. References

[1] Fitzgerald, M. J. and J. Folan-Curran **"**Clinical Neuroanatomy and Related Neuroscience." 4th edition, Saunders, New York, 2012

[2] Alfred, P., P. Husar, G. Henning, and H. Rodder "Phase estimation of visual evoked responses" IEEE Trans. Biomed. Eng, 50, pp.324-333, 2003.

[3] Chiappa, H. K **"**Evoked Potentials in Clinical Medicine", 2nd Edition, New York, Raven Press, 1999.

[4] Mishra U K, Kalitha J. "Clinical Neurophysiology-Nerve conduction Electromyography Evoked potentials", 3rd Edition, Elsevier, New Delhi, 2015.

[5] Liveson J A, Dong M M**.** "Laboratory Reference for Clinical Neurophysiology" Philadelphia, Davis Company, 1998.

[6] Mitchell, B., B. Michael, B. Colin, M. Anne, and R. John "Guidelines for Calibration of Stimulus and recording Parameters Used in Clinical Electrophysiology of Vision (Revised ISCEV)" 2009.

[7] John G. Proakis and Dimitris K Manolakis, " Digital Signal Processing Principles, Algorithms & Applications", 4th Edition, Pearson, 2014

[8] Omry Paiss & Gidion F.Inbar "Autoregressive modeling of surface EMG and its spectrum with application to fatigue" IEEE transactions on Biomedical Engineering, Vol. BME-34, No.10, pp.761-770, October 1987 .

[9] L. Leo chen , Radhika Madhavan, Benjamin I. Rapport and Willum S. Anderson. "Real time brain oscillations detection and phase locked stimulation using autoregressive spectral estimation and time-series forward prediction" IEEE Transactions on Biomedical Engineering, 60, No.3, March-2013.

[10] Akaike, H. **"**A new look at the statistical model identification" IEEE Trans. Automat. Contr. 19, pp.716-723, 1974.

[11] Kay, S. M. and S. L. Marple "*Spectrum analysis: A modern perspective*" Proc. IEEE, 69**,** pp.1380-1419, 1981.