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Natural resonance frequency identification for sea waves and EEG epileptic patients using Pade approximation and neural network

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ABSTRACT

Pade method is used in the spectral domain estimation to classify both the remote sensing and the biomedical signals. The first example presented from remote sensing is the sea wave classification while the second example depicted from biomedical engineering field is the Epilepsy seizure type classification. Feature extractions of both the Global Navigation Satellite Systems (GNSS) signal and the epilepsy seizure from a human Electroencephalograph (EEG) signal are based on the poles location of the signal.

1. Introduction

Signal modeling is a technique for building scientific model of the real signals. The procedure of framework demonstrating requires an estimation technique is applied to estimate value for the adjustable parameters in the required model structure. At long last, the assessment of the evaluated model to check whether the model is sufficient for your application needs. In this research, Pade technique is utilized and applied for two distinct applications.

First application is about remote sensing It has been generally shown that signal transmitted from GNSS groups of Global Navigation Satellite System like (Global Position Systems (GPS) can be utilized not just for positioning, likewise, for remote sensing. Specifically, the outside of the sea convey data about the ocean surface makes dissipated GNSS flag, and can be abused to locate its geophysical properties (Sanei et al., 2007). It is characterized as GNSS-Reflectometry, speaks to an imaginative way to deal with sea remote (Mesbah and Boashash, 2004). It is called attention to that GNSS-R for oceanography principally targets examining three significant geophysical parameters, to be specific directional Mean Square Slope (MSS), Significant Wave Height (SWH) and Mean Sea Level (MSL). Subsequently, GNSS-R has both dispersed metric (ocean unpleasantness, wind speed and course) and altimetry (SWH and MSL) applications. Amazing worldly testing, worldwide inclusion, and long haul GNSS mission lifetimes are among the components of GNSS signals which strategy alluring, and especially reasonable for watching the sea surface, which is profoundly factor in reality, The space crucial by Surrey Satellite Technology Ltd UK-DMC is utilized to measure the ocean surface unpleasantness utilizing GPS-Reflected payload and a remote detecting satellite transport Fig. 1 (Sanei et al., 2007; Mesbah and Boashash, 2004; James et al., 2018; Kannathal et al., 2019; James, 2007; Iscan et al., 2011; Kannathal et al., 2005; Kiymik et al., 2004; Liu et al., 2002).

Another Application, Epilepsy issue happening inside the human mind influences just around 1% of the United States populace. It is described by an unexpected strange terminating of neurons prompts intermittent and nonstop Seizures (Lopes and da Silva, 1975). The sorts of Seizures are general or fractional which will be clarified.

Summed up seizures are exhibited as loss of cognizance. The explanation of this kind of epilepsy is because of concurrent seizures that consequences of cerebrum halves of the globe unusual exercises. Incomplete seizures are all the more prompting loss of memory, and engine conduct. These seizures happen at the piece

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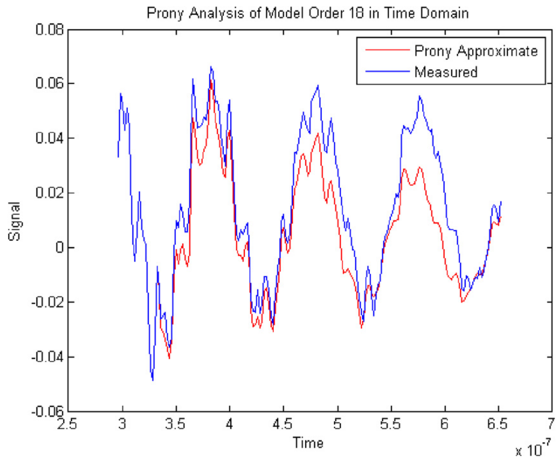

Fig. 1. Original signal and reconstructed signal.

of the mind called epileptogenic center. That is the reason called central epilepsy as well. Epileptic seizures will spread from type to another sort for instance the central to sum up seizures. Fig. 2 shows the contrast between the incomplete and general EEG chronicles (Han et al., 2018).

The most well-known database for epilepsy is MIT-BIT (Minfen Shen and Chuan How Lin, 2010) which gathered at the Children's Hospital Boston. Subjects (5 guys, ages from 3 to 22; and 17 females, ages from 1.5 to 19) were recorded for in excess of twenty four hours for the 23 patients without reflection (Chisci, 2010).

Ictal period is made out of a nonstop release of EEG waveforms. It has a variable sufficiency and recurrence spike and sharp wave edifices, cadenced hyper synchrony. Between ictal has period's electro mind latency seen over length shorter than the normal term of these irregularities during ictal period. EEG examination of patients experiencing epilepsy for the most part depends on between ictal discoveries. In those between ictal EEG chronicles, epileptic seizures are typically enacted with photograph incitement, and different strategies. In any case, one shortcoming of these incitement systems is incited epileptic seizures and not really has a similar conduct as the unconstrained ones. The presentation of long haul video-EEG accounts has been a significant achievement giving not just the likelihood to catch and investigate ictal occasions, yet additionally adding to important clinical data, particularly in those applicants assessed for epilepsy medical procedure. Preceding the appearance of compact recording gadgets, all EEG recording occurred in uncommon medical clinic units. The presentation of convenient account frameworks (walking EEG), in any case, has permitted outpatient EEG recording to turn out to be increasingly normal. This strategy has focal points that patients are recorded in their typical condition without the decrease in seizure recurrence as a rule seen during a long (and costly) inpersistent sessions (McSharry et al., 2003; Michel et al., 1999; Miwakeichi et al., 2004; Aarabi et al., 2006; William and Evans, 1983; Khawani and Bajwa, 1975; El-Hefnawi, 1996; El-Hefnawi and Mossaly, 1996; El-Hefnawi, 1996; El-Hefnawi, 1994; El-Hefnawi, 1994; El-Hefnawi et al., 1975; El-Hefnawi, 1975; Bani-Hassan et al., 2009; Marwa and El-Hefnawi, 2015; Theodoridis, 2010; Elsayed et al., 2012; Elsayed et al., 2015).

Strange states essentially saw in neurological scatters like seizures in epilepsy. Latest examine centers around broadly accessible databases, which are quickly portrayed from MIT-BIT (El-Hefnawi, 1996). This database, gathered at the Children's Hospital Boston, comprises of EEG chronicles from pediatric subjects with obstinate seizures. Subjects were checked for as long as a few days following withdrawal of hostile to seizure drug to portray their seizures and survey their bid for careful intercession. The recorded EEG signal was gathered from 22 subjects (5 guys, ages from 3 to 22; and 17 females, ages from 1.5 to 19) (Chisci, 2010). A study on epilepsy seizure EEG signal demonstrating is accessible in writing (James, 2007; Iscan et al., 2011; Kannathal et al., 2005; Kiymik et al., 2004; Liu et al., 2002). AR model is the most widely recognized method utilized for EEG displaying since the element extricated can be effectively distinguish the epileptic signal dependent on its poles.

Fig. 3 shows the 8 s time of Epilepsy at EEG cathodes C3-C2, C3-O1, C2-C4, Fp1-T3, Fp2-T4. The high recurrence signals are the sign of her epilepsy seizures.

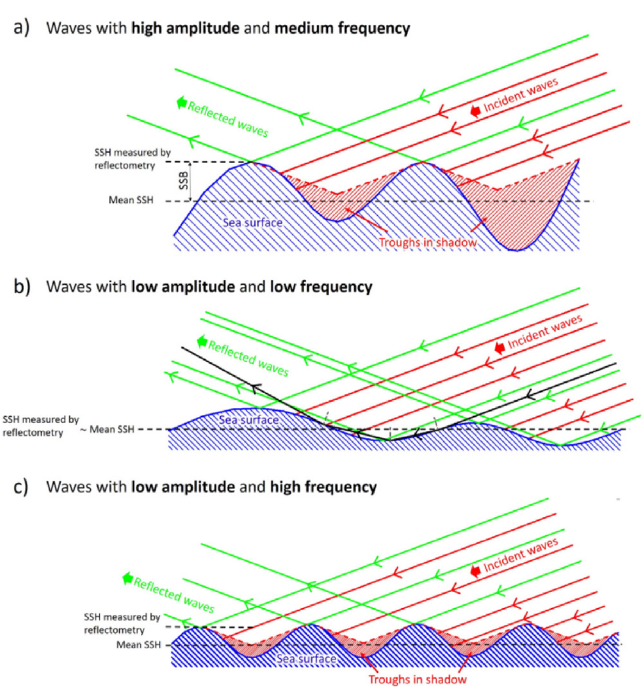

Fig. 2. Different sea waves W1, W2 and W3 consequently.

2. Pade approximation

The Padé estimate is a balanced capacity (El-Hefnawi and Mossaly, 1996) that can be thought of as a speculation of a Taylor polynomial. A normal work is the proportion of polynomials (El-Hefnawi, 1994; Marwa and El-Hefnawi, 2015). Since these

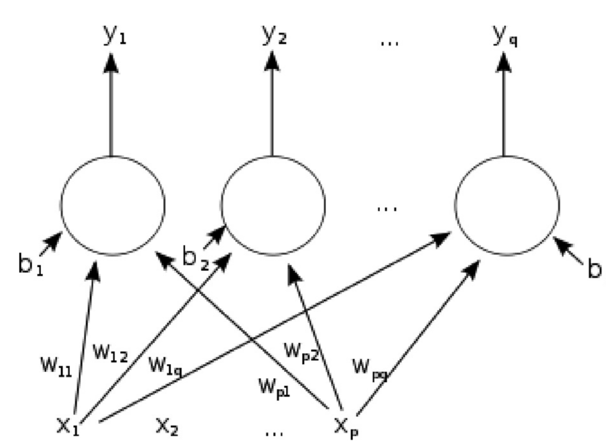

Fig. 3. Functional description of multilayer perceptions (MLP).

capacities just utilize the basic number juggling activities, they are anything but difficult to assess numerically. The polynomial in the denominator enables you to surmised capacities that have sound singularities.

All the more unequivocally, a Padé estimation of request to a scientific capacity at a standard point or shaft is the More précised, a Padé approximation of order $n,\ d$ to an analytic function $f(x)$ at a regular sample or pole x_0 is the rational function $P(x)/Q(x)$ where $P(x)$ is a polynomial of $n$degree, $Q(x)$ is a polynomial of degree$d$. If d=n, the new equation is called a diagonal Padé approximation of the order$n$.

Let$f(x)$ be the EEG signal, it shall be rewritten as:

$$f(x) \cong \frac{P_n(x)}{Q_d(x)} \tag{1}$$

This EEG signal is Z samples formulated,

$$f(x_i) \cong \frac{P_n(x_i)}{Q_d(x_i)} \quad i = 0,\ 1, \ldots, Z-1 \tag{2}$$

where,

$$P_n(x_i) = \sum_{\alpha=0}^{n} a_\alpha x_i^\alpha \quad i = 0, 1, 2, \ldots, D-1, \tag{3}$$

$$Q_d(x_i) = \sum_{\beta=0}^{d} b_\beta x_i^\beta \ i = 0, 1, 2, \ldots, D-1, \tag{4}$$

where, $a,\ b$, are coefficients to be determined. Equation (1) can be rewritten in the following,

$$f(x_i). \sum_{\beta=0}^{d} b_\beta x_i^\beta = \sum_{\alpha=0}^{n} a_\alpha x_i^\alpha \tag{5}$$

Let $b_0 = 1$ (linear prediction constrains). Equation (5) shall be implemented as,

$$f(x_i) = \sum_{\alpha=0}^{n} a_\alpha x_i^\alpha - \sum_{\beta=1}^{d} f(x_i) b_\beta x_i^\beta \tag{6}$$

The application of equation (6) from points $0\ \ to\ \ Z-1$, Z equations will be written in matrix form,

$$[F] = [X].[A] \tag{7}$$

where,

$$[F] = [f_0, f_1, f_2, \ldots, f_{D-1}]^T \tag{8}$$

$$[A] = [a_0, a_1, a_2, \ldots, a_n, b_1, b_2, \ldots, b_d]^T \tag{9}$$

$$[X] = \begin{bmatrix} 1 & x_0 & \ldots & x_0^n & -f_0 x_0 & -f_0 x_0^2 & \ldots & -f_0 x_0^d \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 1 & x_i & \ldots & x_i^n & -f_i x_i & -f_i x_i^2 & \ldots & -f_i x_i^d \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 1 & x_{D-1} & \ldots & x_{D-1}^n & -f_{D-1} x_{D-1} & -f_{D-1} x_{D-1}^2 & \ldots & -f_{D-1} x_{D-1}^d \end{bmatrix} \tag{10}$$

The unknown coefficients $[a_0, a_1, \ldots, a_n, b_1, \ldots, b_d]$ shall be implemented by Gauss Technique for $Z = n + z + 1$, or using the least squares method for $Z > n + z + 1$.

At long last, the denominator of the polynomial zeros are determined, posts the capacity, shall be highlight group of the EEG signal, encouraged to the ANN system classifier model to distinguish heart arrhythmias and settle on the symptomatic choice.

3. Classification technique

Classifier model dependent on artifetial neural systems Artifetial Neural Network (ANNs) was used all through this examination. In an ANNs structure, numerous straightforward, nonlinear preparing components, called neurons will be interconnected by means of weighted neurotransmitters to frame a system. The capacity of every neuron is to figure a weight total of all neurotransmitter inputs, and subtract the aggregate from the predefined inclination, and pass the outcome through a capacity whose yield goes somewhere in the range of 0 and 1. Fig. 3 shows the practical depiction of a single neuron, that are the information, weight, inclination, net capacity, move work and the yield of neuronseparately.

The ordinates f_i are known by taking a_p = 1 (linear prediction constraints), equation (9) the most part can be unravelled straightforwardly for t_a if D = 2P, or illuminated roughly by using the least square method if D > 2P.

In the wake of registering a's coefficients, the X's can be determined as the base of condition (3). Condition (2) at that point turns into a lot of direct conditions in R. Consequently, R can be established from the principal P conditions (2).Also; the least square procedures can be applied to the whole set Experimental.

4. Results and discussions

The Multilayer Perceptions (MLP) consists of three layers, the first layer is the input layer neurons which are equal to the poles number 400, the second layer is the hidden layer, and finally the five neurons output layer. The training function used is the one-step secant back propagations to adapt the weight and the bias of the network. The transfer function used is the Tan-Sigmoid function in the first, and pure linear function is used in the output layer. Pade method is faster compared to the Auto regression (AR) model and relevance vector machine (RVM) by Min Han (Minfen Shen and Chuan How Lin, 2010), which depicts that modeling is based on poles location and number of poles could be used instead of AR model where the Number of poles makes computation faster than AR model, which based on both poles and zeros. The Pade method is better than AR and RVM because the Pade method basis is not sinusoidal signal but an exponential signal.

In the training phase the adaptation of the input and target are based on the poles location which is distributed based on the epilepsy type. After training, The appropriate weights to map the inputs to the desired outputs is reached while an optimum order of the polynomial is chosen in equation (1) that results in reducing the Mean Square Error (MSE).

In the testing phase, the performance of the MLP classifier using the Man square error (MSE) technique where the error is the difference between the target and actual network output. It is possible minimize the error by increasing the number of poles up to 30 to get the minimal error.

The EEG signal was obtained from the MIT-BIH Database (El-Hefnawi, 1996) which is used for this work. Data Sets was composed of 23 epilepsy cases with sampling rate at 250 sample/sec. Applying Pade Method to epilepsy yields reliable results

The Multilayer Perceptions (MLP) is produced using three layers; the information layer is equivalent to the shafts number, 400 neurons in the shrouded layer, and five neurons at the yield layer,

Table 1
Classification Using THE NEURAL Network.

	Trained Data size	TN	TP	FN	FP
NR	23	23	–	–	–
EP	23	–	23	–	–

one for each class. Table 1 shows the classification the 23 patients' epileptic and normal cases.

5. Conclusion

The signal model depends on the area of the poles of the signal. When we increase number of poles, we shall decrease the error because of signal reconstructed and get faster response. The outcome MSE diminishes exponentially. It is conceivable to expand the request for the recreated signal polynomial up to 400 to persuade least error to be very near zero.

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