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Research Paper

Natural resonance frequency identification for remote sensing and biomedical engineering using Prony method and fuzzy logic

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ABSTRACT

Prony method is applied 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

System identification is a technique widely used to construct an Input Output Dynamic System which is response is measured for both input and output signals followed by the model structure construction. Consequently, the estimation method is applied to estimate the adjustable parameters values in the model structure. Finally, the model will be evaluated to see if the model is adapted to the application requirements. Prony method has been employed to various eras, especially radar target identification, EM waves, biomedical processing, and wideband frequency response of antennas (Sanei and Chambers, 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; Lopes and da Silva, 1975; Han, 2018; Shen and Lin, 2010; Chisci, 2010; McSharry et al., 2003; Michel et al., 1999; Miwakeichi et al., 2004; Aarabi et al., 2006; Evans, 1983; Khawani and Bajwa, 1975; MIT-BIT datasets; El-Hefnawi, 1996; El-Hefnawi and Mossaly, 1996; El-Hefnawi, 1996; El-Hefnawi, 1994; El-Hefnawi, 1994; El-Hefnawi, 1975; El-Hefnawi, 1975; Bani-Hassan and Elhefnawi, 2009; Marwa and El-Hefnawi, 2015; Theodoridis, 2010; Elsayed et al., 2012; Elsayed et al., 2015). In this research, Prony method is used and applied for two different applications with fuzzy logic support: Remote sensing and Biomedical Engineering.

First application is about remote sensing. A series of global navigation satellites (GNSS-R) was developed for monitoring the weather and sea waves. For example, UK-DMC British space satellite mission.

Another Application, Epilepsy disorder occurring inside the human brain affects only around 1% of the world wide population. It is classified by a sudden malfunction ignition of neurons leads to recurrent and continuous Seizures (Sanei and Chambers, 2007). The types of Seizures are general or partial which will be explained.

Generalized seizures are presented as loss of consciousness. The reason of this type of epilepsy is due to simultaneous seizures that results of brain hemispheres abnormal activities. Partial seizures are more leading to loss of memory, and motor behavior. These seizures occur at the part of the brain called epileptogenic focus. That is why called focal epilepsy too. Epileptic seizures will spread from type to another type for example the focal to generalized seizures (Mesbah and Boashash, 2004).

The most common database for epilepsy is MIT-BIT (James et al., 2018) which collected at the Boston Hospital University and Ain Shams University Specialized Hospital has another source of

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datasets. About 100 patients filtered to 5 patients only can be clinically filtered (Subject 5 males) (James et al., 2018).

The area of the focal epilepsy can be identified by the location of EEG electrodes, of almost third of all epilepsy patients with partial seizures, is focused in the temporal lobe that is why called temporal lobe epilepsy

The EEG epilepsy recordings show two kinds of mal activity: inter-ictal which defined as abnormal signals appeared among epileptic seizures and the other type is called ictal seizure which is the activity appeared while an epileptic seizure occurs. The EEG signature of an inter-ictal activity is irregular transient waveforms, as isolated spikes or complicated spike-wave. Ictal period is composed of a continuous discharge of EEG waveforms. It has a variable amplitude and frequency spike and sharp wave complexes, rhythmic hyper synchrony. Inter-ictal has limited time of electro mind inactivity which is observed over short duration of time compared to the average duration of these abnormalities during ictal period. EEG analysis of patients suffering from epilepsy usually relies on inter-ictal findings. A simulation using video stream will be applied to those epileptics patient in order to trigger the nter-ictal EEG seizures, epileptic seizures.

Anomalous states basically saw in neurological issue like seizures in epilepsy. Latest research centers on generally accessible databases, which are quickly depicted from MIT-BIT (MIT-BIT datasets). Ain Shams University Specialized Hospital has another datasets of 100 patients separated to 5 patients just can be clinically diagnosed (Subject 5 males). 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 demonstrating since the element extricated can be easily used to distinguish the epilepsy sign dependent on its shafts and zeros.

Fig. 1 shows the 8 s time of Epilepsy at EEG anodes C3-C2, C3-O1, C2-C4, Fp1-T3, Fp2-T4. The high recurrence sign is the sign of her epilepsy seizures. Fig. 2 depicts the GNSS-R signals at different 3 types of sea waves. The first wave W1 is characterized by high amplitude and medium frequency sea wave. The second wave W2 is characterized by low amplitude and low frequency. While, the third wave W3 is characterized by low amplitude and high frequency.

2. Prony method

Prony Method is a method used for modeling f(t_i) at D data sample points and is equated to a damped exponential functions linear combination (Evans, 1983).

Beginning with the basic derivation of it, it is

$$f(t_j) \cong \sum_{\beta=1}^{P} R_\beta \exp\left(s_{\beta j}\right), \tag{1}$$

And,

$\beta = 1, 2, 3, \ldots, P,$

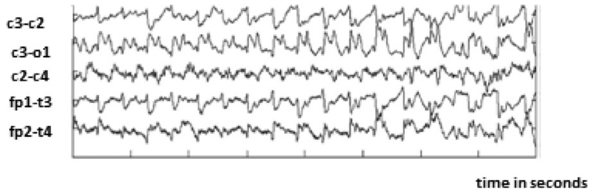

Fig. 1. EEG Electrodes signal C3-C2, C3-O1, C2-C4, Fp1-T3, Fp2-T4 shown in order from top to bottom against time for 8 s duration.

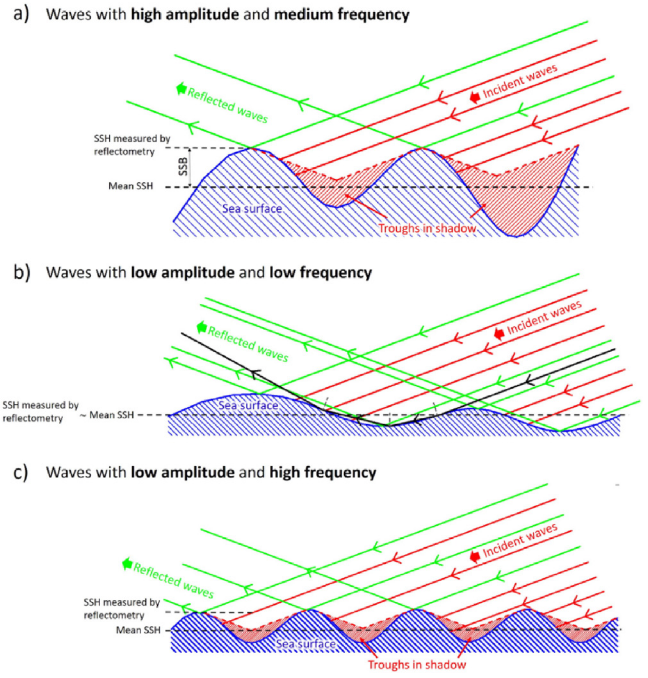

Fig. 2. Different Sea waves W1, W2 and W3 consequently.

$j = 0, 1, 2, 3, \ldots, D-1.$

where $f(t_i)$ is the Epileptic signal and D is the sampling at points $t_0, t_1, t_2, \ldots, t_{D-1}$, s_α is defined as the β^{th} pole, and R_β is defined as the β^{th} residue's amplitude.

It is essential to specify equation (1) in discrete data samples at σt intervals, thus,

$$\begin{aligned} f(t_i) &= \sum_{\beta=1}^{P} R_\beta \exp(s_\beta i \delta t), \\ f(t_i) &= \sum_{\beta=1}^{P} R_\beta (X_\beta)^i, \\ X_\beta &= \exp(s_\beta \delta t) \end{aligned} \tag{2}$$

where s_β: complex number and the poles$s_\beta$of the EEG signal can be directly calculated as,

$$s_\beta = \frac{1}{\delta} \ln(X_\beta) \tag{3}$$

Where R_s are defined as the damping coefficients, and the size of the sampling interval is δt. The above sets of nonlinear equations (2) have both sets of unknowns X_β's and R_β's.

Using Prony Method procedure, one can define a polynomial $A(N)$ of order P in the variable having the same β roots appearing in equations (1) to (2), thus,

$$A(N) = a_0 + a_1 N + a_2 N^2 + \ldots + a_P N^P \tag{4}$$

Equation (3) can be written in terms of its roots as,

$$A(N) = (N - X_1)(N - X_2) \ldots (N - X_P) = 0 \tag{5}$$

where X's: The roots of the above equation.

The coefficients in equation (4) can be calculated, the first equation (2) will be multiplied by the first coefficienta_0, and the second with $a_1$and so on till the last coefficient a_P which resulted in a set of the following equations:

$$\begin{aligned} a_0 f_0 &= a_0 Y_1 + a_0 Y_2 + \ldots + a_0 Y_P \\ a_1 f_1 &= a_1 Y_1 X_1 + a_1 Y_2 X_2 + \ldots + a_1 Y_P X_P \\ a_2 f_2 &= a_2 Y_1 (X_1)^2 + a_2 Y_2 (X_2)^2 + \ldots + a_2 Y_P (X_P)^2 \\ \ldots & \quad \ldots \quad \ldots \quad \ldots \quad \ldots \\ a_P f_P &= a_P Y_1 (X_1)^P + a_P Y_2 (X_2)^P + \ldots + a_P Y_P (X_P)^P \end{aligned} \tag{6}$$

Adding the above set of equations (5), yields,

$$A(X_1) + A(X_2) \ldots + A(X_P) = f_0 a_0 + f_1 a_1 \ldots + f_P a_P \tag{7}$$

where $A(X_\beta)$ is defined in equation (4), X_β is the roots of A, thus, equation (6) yields,

$$f_0 a_0 + f_1 a_1 + \ldots + f_P a_P = 0 \tag{8}$$

A set of $D - P - 1$ additional equation can be similarly obtained by repeating the steps explained above, starting fromf_1 to $f_{(D\text{-}P\text{-}1)}$, producing the following set of equations,

$$\begin{aligned} & f_0 a_0 + f_1 a_1 + \ldots + f_P a_P = 0 \\ & f_1 a_0 + f_2 a_1 + \ldots + f_{P+1} a_P = 0 \\ & \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \\ & f_{D-P-1} a_0 + f_{D-P} a_1 + \ \ldots \ + f_{D-1} a_P = 0 \end{aligned} \tag{9}$$

Since the ordinates f_i are known, and by taking $a_p = 1$ (limitation of the linear predictor), equation (9) overall can be found for $t_a$if $D = 2P$, or approximated by using the technique of least square if $D > 2P$.

Following the computing of a's coefficients, the X's can be calculated as the root of equation (3). Equation (2) then becomes a set of linear equations in R. Then, R can be founded from the first P equations (2). In addition; the least square techniques can be applied.

3. Results and discussion

The EEG sign was gotten from the MIT-BIH Database (Khawani and Bajwa, 1975) which is utilized for this work. Informational indexes was made out of 22 epilepsy cases with examining rate at 250 example/sec. Applying Prony Method to epilepsy yields dependable outcomes. An ideal request of the polynomial is picked in condition (1) that outcome in diminishing the Mean Square Error (MSE) (shown in Fig. 3 and Fig. 4). It is conceivable to build the request for the reproduced sign polynomial up to 30 to get negligible mistake. Instances of the epileptic signal control unearthly are appeared in Fig. 5 and Fig. 6.

If we compare this new method to the RVM method employed by Min Han (Han, 2018), one finds that Prony method is faster compared to the AR model. The modeling is based on poles location only and fuzzy system could be used instead of RVM. Number of poles makes computation faster than AR model, which based on poles and zeros. The Prony method is better than AR because the Prony method basis is exponential signal not sinusoidal signal.

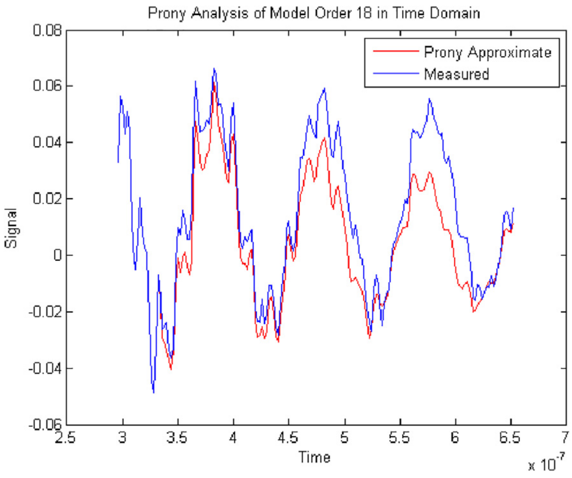

Fig. 3. Original and reconstructed EEG signal.

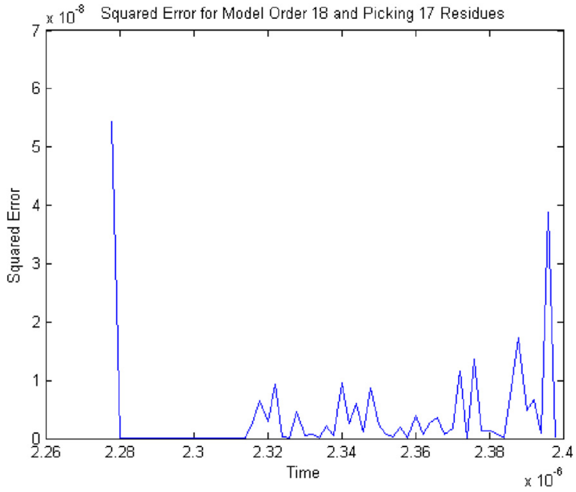

Fig. 4. Errors due to signal reconstruction.

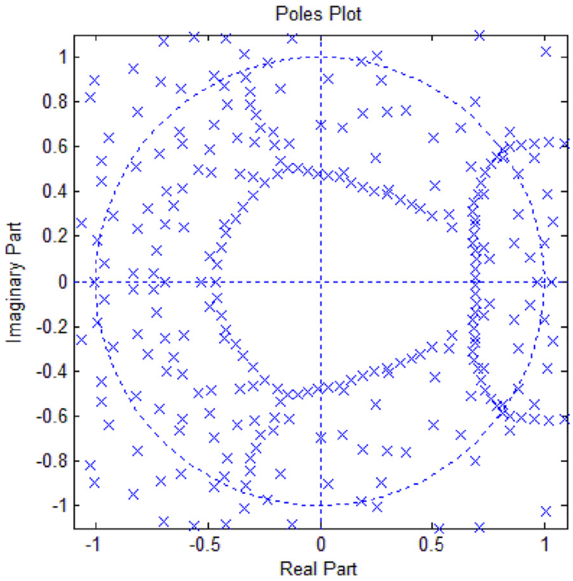

Fig. 5. Poles location of a normal patient.

In this decade, approximated rationale has an assortment of utilizations particularly for remote detecting and space applications. Table 1 shows the quantity of sign utilized in preparing and testing periods of all epilepsy classes where the grouping aftereffects of classifier model of all classes are clarified. The precision, of the classifier model achieve 100%.

It can be shown from Fig. 7 that the poles appear on the circumference of the contour which intersects the real axis at 0.2 and the imaginary axis at 0.4 where poles around 0.2 radiuses for epilepsy signal. This region will be the fuzzy rule of interest. Fig. 8 shows poles location for different type of sea waves that the conjugate poles closer to x axis has a low amplitude sea wave and the conjugate poles closer to the unit circle has a higher sea wave amplitude.

Table 1 depicts the fuzzy range of the sea waves based on amplitude and frequency. W2 mapped to the low amplitude and low frequency while W3 mapped to high amplitude and frequency.

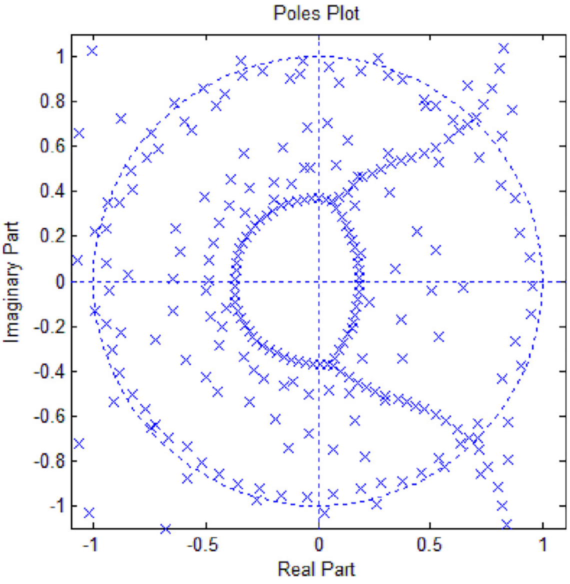

Fig. 6. Poles location of an abnormal patient.

Table 1
Classification results using fuzzy for training data.

	Low Amplitude Low Frequency	Low Amplitude medium Frequency	High Amplitude High Frequency
W2	X		
W1		X	
W3			X

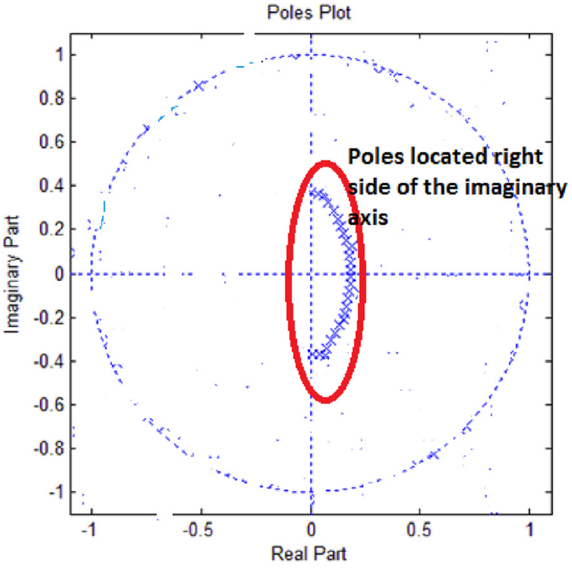

Fig. 7. Poles location of the abnormal patient (ictal epilepsy signal).

4. Conclusion

Prony Method is utilized to depict the poles of the GNSS-R sign and EEG signal. Poles of the GNSS-R are utilized to demonstrate this ocean waves while the EEG to show the epilepsy issue. New poles show up on account of epilepsy while different poles location from ordinary EEG signal.

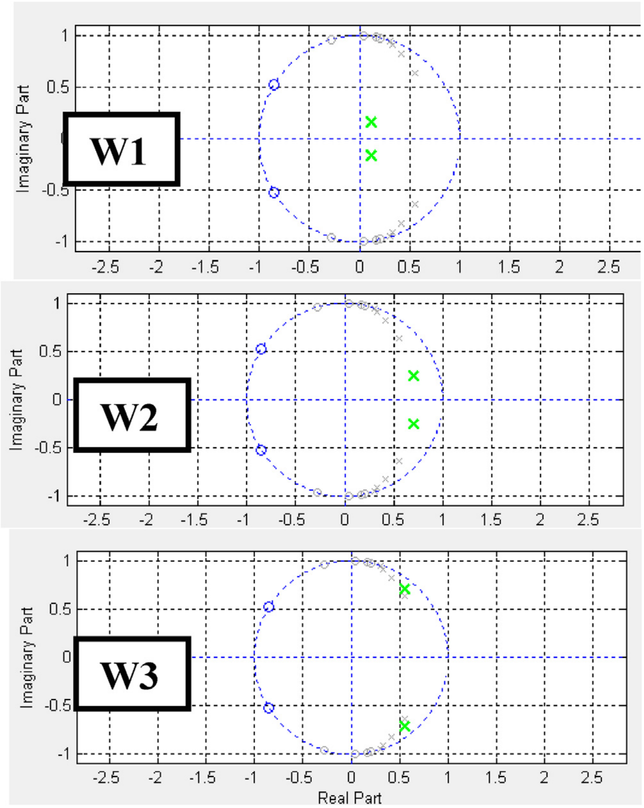

Fig. 8. Poles location of different sea waves W1, W2 and W3.

The signal model depends on the areas and number of poles. As the quantity of poles expands, the MSE diminishes exponentially, along these lines decreasing the mistake of the reproduced signal. With the utilization of approximated rationale, the request for the reproduced signal polynomial can be reduced to 30 rather than 400. Thus, the mean square error will be exceptionally near zero.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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