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Middle Phase of Seizure and Seizure-free EEG Signals Classification Using Fractional Pseudo Controller: Linear Forecasting Approach

Mohammad Fiuzy*, Seyed kamaleddin Mousavi Mashhadi

School of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran

Keywords

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Seizure,
Support vector machine,
Fractional Forecasting.

Abstract

In this paper, a technique is shown for electroencephalogram (EEG) signal grouping based on the fractional-arrange mathematics. This technique, named as the fractional linear forecasting (FLF) is utilized to display the middle phase of seizure (Ictal Pahse) and seizure EEG signals. It is discovered that the displaying blunder vitality is high considerably for ictal EEG signals contrasted with sans seizure EEG signals. In addition, it is realized that middle phase of seizure (Ictal) EEG signals have higher energy than sans seizure EEG signals. These two parameters are then given as contributions to prepare a support vector machine (SVM). The prepared SVM is then used to group an arrangement of EEG signals into middle phase of seizure (Ictal) and without seizure classifications. It is discovered that the proposed technique gives an order forecasting of 95.33% when the SVM is organized with the Radial Basis Function (RBF) kernel.

1. Introduction

Epileptic seizures are the after effect of anomalous over the top or synchronous neural action in the mind. One of the broadly used methods to evaluate mind movement is through the electroencephalogram (EEG) signals. Recognition of epileptic seizures utilizing the EEG signals is imperative for the determination of epilepsy [1]. Amid epileptic seizures real changes happen in a patient's EEG motion because of synchronous electrical movement of the neurons. One of the clear qualities of seizure EEG signal is the occurrence of spikes and sharp waves [2]. Discovery of seizures using EEG signals is required in both diagnostics and treatment. The parameters separated from EEG signs can be utilized as valuable diagnostic highlights for programmed identification of epileptic seizure [3]. Unusual parameters in consideration of the fourier change are commonly utilized highlights for identification and arrangement of epileptic seizure signals [4, 5]. Notwithstanding, the basic assumption of the Fourier change based examination is that the signal being analyzed is stationary. Past examinations have demonstrated that the frequency segments of EEG signal change after some time i.e., the EEG signal is a non-stationary process [6– 10]. A few time– frequency domain based strategies have been created for location of epileptic seizure from EEG signals. These techniques incorporate the short time Fourier change [11], the wavelet transform [12, 13], multi-wavelet change [14], the smoothed pseudo-Wigner– Ville distribution [15], and the multi fractal investigation and wavelet trans-frame [16,17]. The enhanced summed up fractal measurement has been utilized for segregating Ictal EEG signals [18]. Recently, empirical mode deterioration (EMD) based techniques for classification of Ictal EEG signals have likewise been accounted for in literature [19-24]. Autoregressive models are additionally used to discover the seizure locations by assessing the power range of epileptic EEG signals [25]. The success of epileptic seizure identification utilizing straight expectation error energy [2] inspired us to utilize partial direct forecast for EEG signal demonstrating. The motivation behind this paper is to characterize a given arrangement of EEG signals into Ictal and Sans seizure classes. Another procedure for EEG signal grouping is displayed which depends on partial request math. The EEG signal is gone through a fragmentary linear forecasting (FLP) channel. Coefficients of the channel are figured by a least squares investigation to get the most ideal model of the signal. A forecast blunder is characterized as the contrast between the modeled signal and the genuine signal. Since the partial linear forecasting has a low-pass nature, it can't precisely display the sharp changes that happen in Ictal EEG signals in this manner expanding the forecasting mistake. The forecast mistake vitality for a set having both Ictal and Sans seizure EEG signals is computed. The expectation error energy and the signal vitality of each signal are given as parameters to prepare a help vector machine (SVM). At that point another set of error and signal vitality esteems is given as contribution to the SVM. The

* Corresponding Author:
E-mail address: mohammad.fiuzy@yahoo.com

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SVM therefore orders the purposes of the new set into Ictal without and seizure classes. The rest of this article is as follows. The second part introduces an introduction to brain signals and electroencephalography. Then the seizure is presented. In the third section, there is a summary of the fractional calculus. Then the Support Vector Machine has been crafted. In the next section, the proposed method and its specifications are presented. Finally, the results of the proposed method are presented.

2. Electroencephalogram (EEG)

Electroencephalography is an electrophysiological monitoring method to record electrical activity of the brain. It is typically noninvasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used such as in electrocorticography. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. [26] In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time,[26] as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus either on event-related potentials or on the spectral content of EEG. The former investigates potential fluctuations time locked to an event like stimulus onset or button press. The latter analyses the type of neural oscillations (popularly called "brain waves") that can be observed in EEG signals in the frequency domain. EEG is most often used to diagnose epilepsy, which causes abnormalities in EEG readings [27]. It is also used to diagnose sleep disorders, depth of anesthesia, coma, encephalopathy's, and brain death. EEG used to be a first-line method of diagnosis for tumors, stroke and other focal brain disorders,[28,29] but this use has decreased with the advent of high-resolution anatomical imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT). Despite limited spatial resolution, EEG continues to be a valuable tool for research and diagnosis. It is one of the few mobile techniques available (e.g. [30]) and offers millisecond-range temporal resolution which is not possible with CT, PET or MRI. Derivatives of the EEG technique include evoked potentials (EP), which involves averaging the EEG activity time-locked to the presentation of a stimulus of some sort (visual, somato sensory, or auditory). Event-related potentials (ERPs) refer to averaged EEG responses that are time-locked to more complex processing of stimuli; this technique is used in cognitive science, cognitive psychology, and psycho physiological research. Figure 1 illustrates a sample of brain signals and how to extract it.

Figure 1. the scheme of EEG [24]

3. Seizure

A seizure is a sudden surge of electrical activity in the brain. A seizure usually affects how a person appears or acts for a short time. Many different things can occur during a seizure. Whatever the brain and body can do normally can also occur during a seizure. The electrical activity is caused by complex chemical changes that occur in nerve cells. Brain cells either excite or inhibit (stop) other brain cells from sending messages. Usually there is a balance of cells that excite and those that can stop these messages. However, when a seizure occurs, there may be too much or too little activity, causing an imbalance between exciting and stopping activity. The chemical changes can lead to surges of electrical activity that cause seizures. Seizures are not a disease in themselves. Instead, they are a symptom of many different disorders that can affect the brain. Some seizures can hardly be noticed, while others are totally disabling. Seizures are changes in the brain’s electrical activity. This change can cause dramatic, noticeable symptoms or it may not cause any symptoms. The symptoms of a severe seizure include violent shaking and a loss of control. However, mild seizures can also be a sign of a significant medical problem, so recognizing them is important. Because some seizures can lead to injury or be evidence of an underlying medical condition, it’s important to seek treatment if you experience them. Neuronal changes are indicated in Figure 2.

Figure 2. The scheme of neuronal changes [25]

A seizure often has four distinct phases: Prodromal Symptoms, Auras, Ictal and Postictal Stages. The first phase, the prodromal stage involves mostly emotional signals. In an aura, alterations in activity, emotions, hearing, smell, taste, visual perception are involved. Auras are actually a small partial seizure that is often followed by a larger event. They usually come a few seconds to a few minutes before the actual seizure. It’s the beginning of the seizure and is seen mostly in partial seizures. The feelings of the aura are often vague and many patients are unable to describe their features. Ictal phases; the middle of a seizure is called the ictal phase. It’s the period of time from the first symptoms (including an aura) to the end of the seizure activity, which correlates with the electrical seizure activity in the brain. Sometimes, the visible symptoms last longer than the seizure activity on an EEG. Postictal Stages; occurs after the ictus or active stage of the seizure. As the seizure ends, the postictal phase occurs. This is the recovery period after the seizure. Some people recover immediately, while others may take minutes to hours to feel like their usual self. An example of a seizure signal is shown in Figure 3.

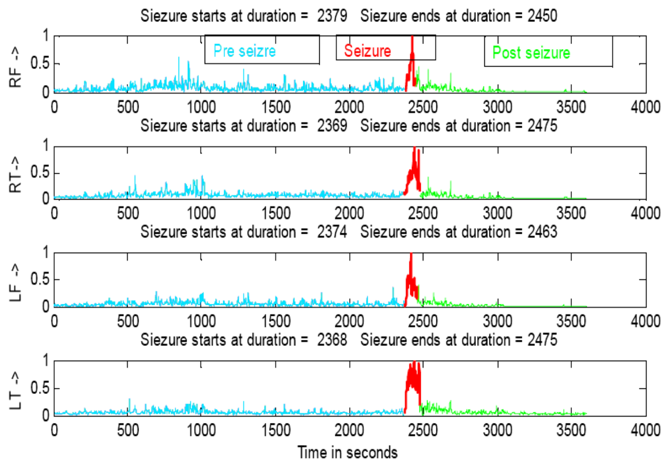

Figure 3. the scheme of seizure signal

4. Fractional linear Forecasting (FLF)

Forecasting Motivated by the adequacy of fractional order modeling techniques over linear forecast (LF) systems for discourse signals [31], we propose to utilize this strategy for demonstrating EEG signals. The point is to have a more exact portrayal of Sans seizure EEG information and subsequently better segregation amongst ictal and without seizure classes. As of late, the EEG signal displaying in view of LP methods has been considered for epileptic seizure recognition [2]. It ought to be noticed that numerous genuine signs and other wonders have been appeared to have naturally fragmentary request flow and thus partial analytics based systems are more appropriate for demonstrating these signs with more noteworthy exactness [32, 33]. Because of these reasons we anticipate that FLP will be a more precise portrayal contrasted with conventional LP strategy. There are numerous approaches to characterize the fractional derivative in the writing. The most normally utilized " Riemann– Liouville " meaning of the fractional derivative of request ρ of a capacity $x(t)$ in Eq. (1) can be communicated as takes after [31, 34].

$$\frac{d^p x(x)}{dt^p} = \frac{1}{\Gamma(m-p)} \frac{d^m}{dt^m} \int_0^t \frac{x(\tau)}{(t-\tau)^{p-m+1}} d\tau \qquad (1)$$

where $m - 1$ is an integer, $m - 1 < p \leq m$, and the Euler's Γ (z) is defined as in Eq. (2)

$$\Gamma(z) = \int_0^\infty e^{-x} x^{z-1} dx \qquad (2)$$

For performing numerical reproductions on a PC the Grünwald– Letnikov estimate of the fractional derivative is commonly utilized. This is characterized as takes after in Eq. (3)

$$D^p\, x(t) = \lim_{h \to 0} h^{-p} (-1)^q \binom{p}{q} x(t - qh) \qquad (3)$$

Presently, like portrayal of yield motion as a direct mix of subordinates of info motion with whole number request in conventional constant time straight framework, we can express a Forecasting EEG motion as a linear blend of its fractional derivatives as shown in Eq. (4) [34]

$$\hat{x}(n) = \sum_{k=1}^{Q} \lambda_k D^{pk} x(n) \qquad (4)$$

Note that here a negative estimation of ρ_k to fractional integral of request ρ_k . We may recast the above condition utilizing Eq. (3) as takes after in Eq. (5)

$$\hat{x}(n) = \sum_{k=1}^{Q} \lambda_k D^{pk} x(n) = \sum_{k=1}^{Q} \gamma_k \phi_k(n) \qquad (5)$$

where γ_k the required FLF parameters .These parameters can be dictated by limiting the energy of expectation mistake. The forecast blunder is characterized by Eq. (6)

$$e(n) = x(n) - \hat{x}(n) \qquad (6)$$

and its energy is given in Eq. (7)

$$\in = \sum_{n=0}^{N-1} \left(e(n)\right)^2 \qquad (7)$$

where N is the quantity of tests in the signal. The point is to decide γ_k while limiting the forecasting error vitality ∈. The above conditions are composed all the more conveniently using framework documentation. Signify the succession relating to fractional essential $\varphi(n)$ *by* $N \times 1$ segment vectors γ_k and the required Figure 5 at below: Coefficients by the segment vector f. At that point we have to comprehend the following condition to get γ_k in Eq. (8)

$$f = (\wedge^T \wedge)^{-1}\ \wedge^T x \qquad (8)$$

where $\wedge = [\rho_1\ \rho_2\ \rho_3\ \ldots.\rho_Q]$. so the proposed method has designed in the below flowchart (Figure 4).

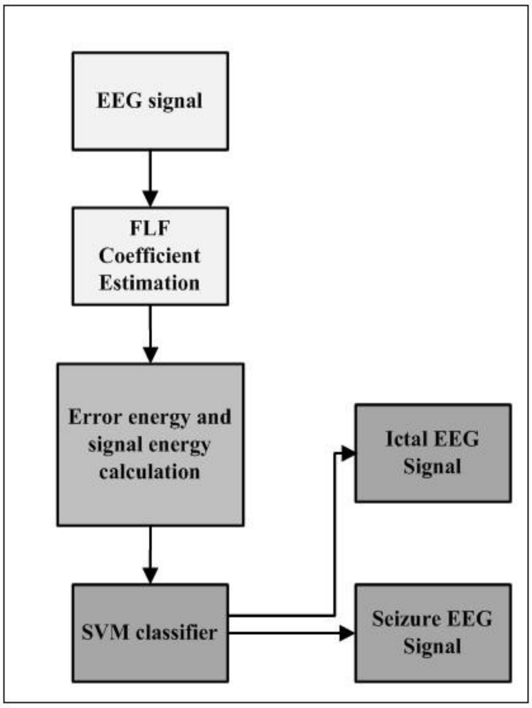

Figure 4. Proposed strategy

5. Support Vector Machine (SVM)

To classify ictal and seizure free EEG signals utilizing forecast blunder vitality and signal vitality we utilize a SVM. The fundamental guideline of a SVM is most effort lessly comprehended for a two-dimensional case [35]. Here we require arranging a progression of information focuses into two distinct classes of information. These two classes can be spoken to by and B. The SVM technique gives a limit H between the two classes with the end goal that the edge is expanded. This implies the separation between the limit and the closest information point in each class is maximal. The closest information focuses are named as help vectors. Given a preparation test set $S = \{ (x_i, y_i), I \ = \ 1 \ldots l\}$, where each sample $x_i \in R^d$ belongs to a class $y: \in \{+1, -1\}$. The limit can be expressed as takes after [31] in Eq. (9)

$$\omega . x + a = 0 \tag{9}$$

where ω is a weight vector and a will be an inclination. At that point the choice function can be utilized to characterize in to two unique classes as takes after in Eq. (10)

$$g(x) = sign(\omega . x + a) \tag{10}$$

with a specific end goal to get the ideal plane we have to in Eq. (11)

$$Minimize \ \frac{1}{2} \ ||\omega||^2$$

$$Subject \ to \ y_i \ [(\omega . x_i) + a] - 1 \geq 0 \, , \quad i = 1,2 \ldots l \tag{11}$$

we may revamp the enhancement issue by the utilization of Lagrange multipliers $\beta_i \ \geq \ 0$ as takes after [31]: Minimize Eq. (12)

$$M(\omega, a, \beta) = \sum_{i=1}^{l} \frac{\beta_i(-1)}{2} \sum_{i,j=1}^{l} \beta_i \beta_j y_i y_j \ (x_i . x_j) \tag{12}$$

Subject to $\beta_i \geq 0 \, , and$

$$\sum_{i=1}^{l} \beta_i y_i = 0$$

At that point, the acquired choice capacity can be given as takes after in Eq. (13)

$$g(x) \ = \ sign \ (\sum_{i=1}^{l} \beta_i y_i (x_i . x) + a) \tag{13}$$

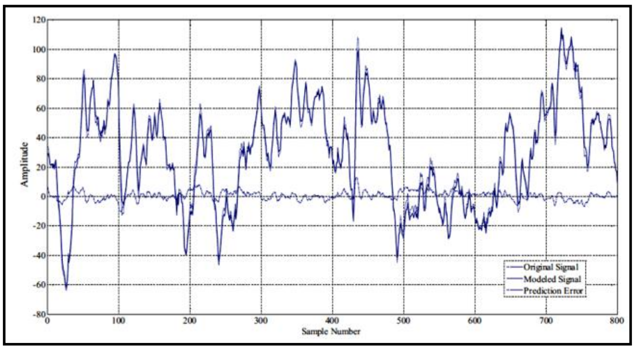

Figure 5. FLF Modeling of seizure – free EEG Signal

On the off chance that the partition into two classes isn't conceivable by a linear boundary then a hyper plane should be made to do linear separation in higher measurements. This is accomplished by utilizing a trans-development $T(x)$ that maps the information from input space to highlight space. If a bit work On the off chance that the partition into two classes isn't conceivable by a linear boundary then a hyper plane should be made to do linear separation in higher measurements. This is accomplished by utilizing a trans-development T(x) that maps the information from input space to highlight space in Eq. (14). If a bit work.

$$M(x, y) \ = \ T(x). T(y) \tag{14}$$

is utilized to play out the change, at that point the fundamental type of SVM can be communicated as takes after in Eq. (15)

$$g(x) = sign \ (\sum_{i=1}^{l} \beta_i y_i M(x_i . x) + a) \tag{15}$$

In this paper we have utilized the kernel functions:

(1) linear part: The straight bit can be characterized as takes after [32] in Eq. (16)

$$M(x, x_i) = \ x^T x_i \tag{16}$$

(2) Polynomial part: The polynomial bit can be characterized as follows [32] in Eq. (17)

where l is the request of the polynomial.

(3) Radial basis function kernel (RBF) . The RBF bit can be defined as takes after [36]

$$M(x, x_i) \ = \ e^{-||x - x_i||^{\frac{2}{2\sigma^2}}} \tag{17}$$

where σ is controls the width of RBF work.

6. Proposed Strategy

The EEG signal is gone through a FLF filter. The channel then calculates the FLF coefficients of the signal utilizing a slightest squares approach. The FLF coefficients are utilized to show the signal according to Eq. (4). The distinction between the genuine signal and the displayed signal is characterized as the forecast mistake.

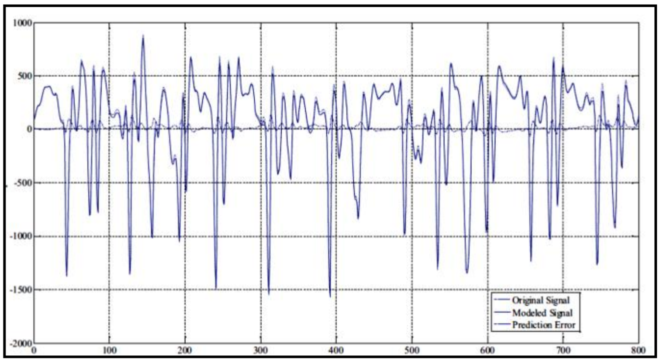

Figure 6. FLF modeling of Ictal EEG signal

The vitality of forecasting blunder is evaluated once the signal displaying is complete. The vitality of the signal is likewise ascertained and this action is rehashed for the whole arrangement of EEG signals. It ought to be noted that the hasty nature or sharp changes in the ictal EEG signals will require high request of FLP with a specific end goal to show the signal. The prerequisite of FLF request will be low for without seizure EEG signals because of nonappearance of driving forces or sharp changes. For the same order demonstrating mistake in the Sans seizure EEG signs will be less compared to Ictal EEG signals. The displaying mistake together with signal vitality causes us to build up an arrangement framework in order to characterize the Ictal and without seizure EEG signals. Next, we choose50% of the signs each from the Ictal class and the seizure-free category and utilize their expectation blunder vitality and signal energy as highlights to prepare a SVM. At last, whatever is left of the forecast error energy and signal vitality information is utilized for arrangement of the EEG signals into Ictal and Sans seizure classes. We change the kernel functions and their parameter esteems utilized for preparing the SVM to get the most noteworthy precision. The execution of the strategy is evaluated through SVM arrangement plots and by computing accuracy (Acc), affectability (SEN), and specificity (SPE) values for the set of classified information. A stream graph of the proposed technique is indicated in Figure 4. Of course, the main point about how to do the proposed method os applying it on the signal that demonstaret as well as its energy behavior in the Figure 7.

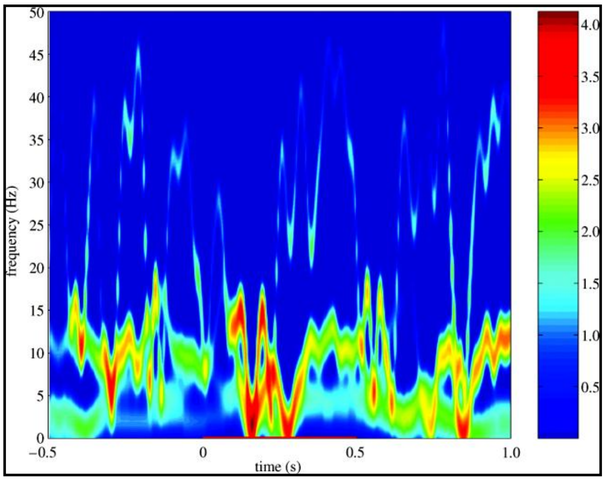

Figure 7. The energy of proposed method

7. Advantages

To check our recommendation we did reenactments on the EEG informational index accessible freely in Sheng et al., study [33]. The informational index comprises of five subsets (denoted as Z, O, N, F, and S) each containing 100 EEG signala, every one having 23.6 s span. In this examination, we have utilized just the subsets F, N, and S to perform reproductions. The signs in the subset F and N have been measured in Sans seizure interims from five patients. Subset F is measured from the epileptogenic zone and N from the hippocampal development of the inverse side of the equator of the mind. The subset S contains seizure action, chose from all chronicle destinations displaying Ictal movement. The examining recurrence of the EEG motions in the informational index is 173.61 Hz. In this work, we have performed displaying on the initial 800 specimens of each signal. To begin with, each of the signs was gone through a fragmentary straight forecast channel and the ideal coefficients were assessed. Next, utilizing these coefficients the expectation blunder vitality for each signal was computed. The blunder vitality and signal energy were given as contributions to prepare a SVM. For preparing half of the data was utilized, the staying half information was kept for classification. The SVM can be prepared utilizing distinctive Kernel capacities and after trial and error it was discovered that the most extreme characterization accuracy of 95.33% was gotten for spiral premise work (RBF) kernel with σ = 0.02. The order exactness comes about for various kernel capacities for each arrangement of information are abridged in Figure 10. The results demonstrate a considerable increment in exactness as we go from the linear piece to the RBF portion work. The characterization test execution of the SVM-classifier can be controlled by calculation of affectability (SEN) and specificity (SPE) alongside precision (Acc). They are characterized as shown in Eqs. (19-21)

$$SEN = \frac{true\ positives}{total\ positives} \times 100 \tag{19}$$

$$SPE = \frac{true\ negatives}{total\ negatives} \times 100 \tag{20}$$

$$Acc = \frac{Correctly\ Classified}{total} \times 100 \tag{21}$$

These qualities were figured for various piece works and are exhibited in Figure 9. The displaying of without seizure and Ictal EEG information for a specimen signal is appeared in Figures 5 and 6 respectively. The arrangement of information into Ictal and Sans seizure classes for RBF bit is appeared in Figures 8,9,10.

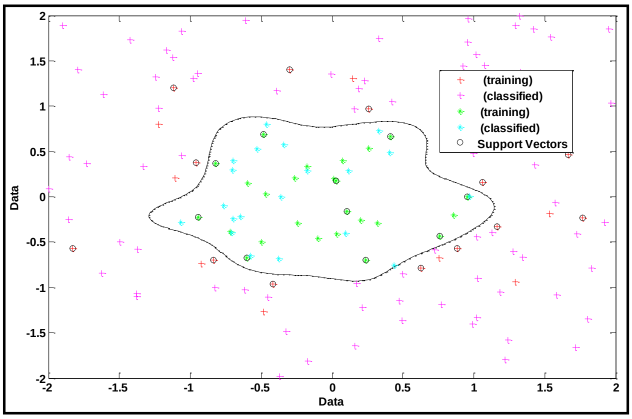

Figure 8. SVM Classifier Plot

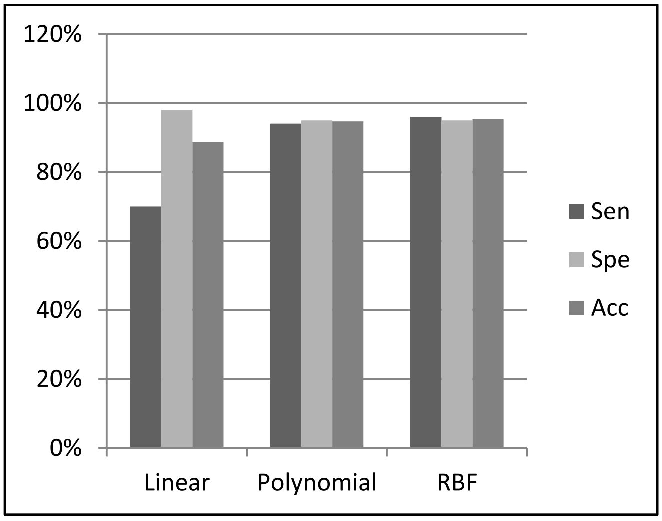

Figure 9. Classification accuracy for different kernel functions and EEG data sets.

* sensitivity, specificity, and precision esteems for various portion capacities.

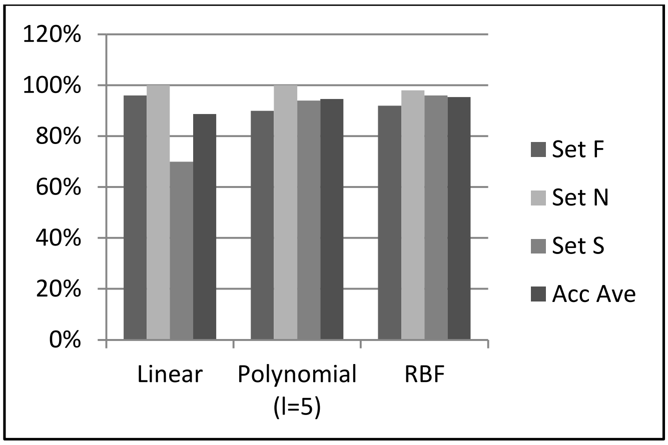

Figure 10. Sensitivity, specificity, and accuracy values for different kernel functions

It is clear from Figure 8 that the proposed method can be used as a diagnostic tool for detecting Ictal EEG signals. In order to evaluate the performance of the proposed method for classification of Ictal and seizure-free EEG signals, a comparison with the proposed method in Altunay et al., study [2] is done. The method proposed has provided average classification accuracy of 94% for classification of Ictal and seizure-free EEG signals, whereas our proposed method provides higher classification accuracy which is 95.33% for classification of Ictal and seizure-free EEG signals. We have com-pared our method for classification of Ictal and seizure-free EEG signals with the method proposed by Altunay et al., with same number of EEG signals of the same data set.

6. Coclusion

FLF is an intense and compelling technique for displaying of EEG signals. The expectation blunder vitality emerging out of this demonstrating and the vitality of signal are utilized as highlights to characterize Ictal and without seizure EEG signals. The arrangement of EEG information utilizing mistake vitality and signal vitality as parameters to the SVM has ended up being effective with a most extreme characterization precision of 95.33%. Consequently, FLF guarantees to end up plainly an essential instrument for biomedical signal handling applications. Enhancements in grouping precision might be conceivable by utilizing other Kernel capacities, for example, Morlet wavelet, Mexican cap and so forth.

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