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Performance Analysis of Various Kernelized SVM Based on HFD and Correlation Dimension During Partial Limb Movement Imagery

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Abstract

Neuroprosthetic devices controlled by EEG are being developed to cater the needs of those who are differently abled. These devices are also finding applications in improving their quality of life. As the EEG signal is fractal in nature, in this paper, we investigate the temporal changes in the fractal dimension and correlation dimension corresponding to partial limb movement imagery, namely: finger movement imagery, distal limb movement Imagery, proximal limb movement imagery. The classification was done by various kernelized support vector machines. A novel Sugeno type fuzzy inference system was developed to evaluate the performance of the classifiers. The complexity measures did vary with time, and had unique trends. This type of analysis would be helpful in calibration of the neuroprosthetic devices on the basis of imagery complexity which depend on the character of the sensorimotor rhythms of an individual for functioning.

1. Introduction

Applications of Chaos Theory and Nonlinear analytical methods helped us to get a closer look into the brain dynamics with the help of EEG signals. This approach relies on a transition from the phase space and trajectory generation. Fractal dimension of the trajectories leading to strange attractors is the measure of the effective number of degrees of freedom in the chaotic dynamical system, thus, quantifying its complexity [8, 9, 10]. Feature extraction is important as it affects classification and computation speed considerably. Complexity measures have been successfully integrated with various domains to exemplify the innate complexity of the data with nonlinear properties, though in this paper it is being used for the first time in partial limb movement imagery based BCI applications. [4]

Brain Computer Interfaces translates the brain activity using efficient pre-processing, feature extraction and classification. Computer interfacing with brain can be broadly categorized into four classes:

(1) Acquisition of the neural activity;

(2) Imagery Extraction of the action pertaining to the particular activity involved;

(3) Implementation of the desired action with the help of the prosthetic effectors; and

(4) Feedback, either through intact sensation like vision, or generated and applied by the prosthetic device [1, 2, 3, 4, 25].

Fractal analysis allows investigation of relevant events which are relatively shorter than those which can be detected by means of other linear and non-linear techniques. Higuchi's Fractal Dimension is an estimation of attractor dimension which is calculated in the time domain as it becomes essential to retrieve maximum information from short time domain data.

2. Details Of The Experiment And Data Description

Mostly investigators use C3, C4 and Cz of the 10-20 electrode system to analyze the complexity of brain signals, since they are placed on the scalp over the motor cortex which is associated with voluntary control of movements. The mining of relevant features which describes the discriminative signal properties still remains to be the primary step after the signal acquisition. Feature mining [11, 12, 23, 25] is the fundamental step for developing an efficient interface. To improve the performance of the classifiers it is crucial to select relevant features associated with the imagery.

This study is based on the recordings of the EEG signal done using NeuroWin EEG Acquisition System designed by NASAN India Pvt. Ltd. Ag/AgCl electrodes were used as the brain interface, and the data was recorded at a sampling frequency of 250 Hz, which was further filtered using an IIR bandpass filter between 0.01 Hz and 35 Hz. 3 channel electrodes: C3, Cz and C4 were selected and were placed according to the International10-20 Electrode placement system. The sensitivity of 100 µV is to be taken and an additional 50 Hz notch filter has been implemented to get rid of the line noise. The sampling frequency of the amplifier was set to 250 Hz, i.e., 250 bits of data were saved for each second. The data was also saved in ASCII format and for further processing of the data MATLAB was used.

This experiment was designed to quantitatively analyze the temporal evolution of the fractal nature of motor imagery through repetitive training of the same subject. The experiment was performed for 9 days on a male subject of 21 years of age, who had no prior exposure to BCI related environment. The feedback session was designed where the subject relaxed on a chair with armrests. The duration of the experiment was 9 days, divided into three phases (each phase corresponding to a week). The intervals between the days were kept constant for all the phases. Each day the participant was asked to perform three sets of tasks. The instructions of the task were given to the participant through an audiovisual stimulus.

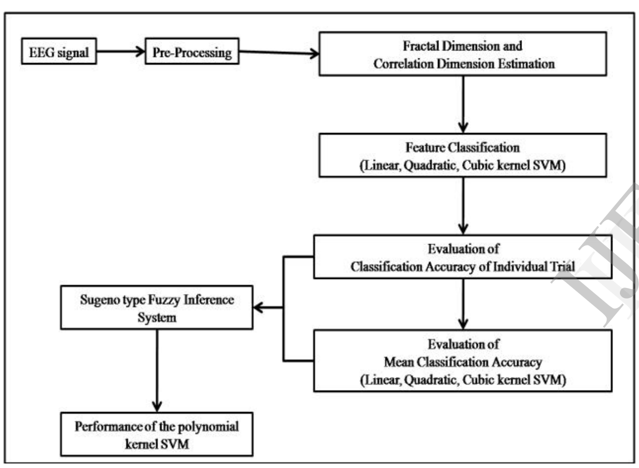

Figure 1: Schematic of the Experimental Methodology.

Each session consisted of 30 trials. In the first session, the participant was asked to imagine self-paced finger movements. The participant performed this task in one session. In the 2nd session the subject imagined self paced distal limb movements, and in the 3rd session motor imagery of self paced proximal limb movement was performed. C3, C4, Cz electrodes were considered relevant for the study. The audiovisual stimuli started with a blank screen for 2 second, followed by an audiovisual cue ('+' with a beep for 2 seconds) which signaled the subject to get ready for the cue about the Limb Type (Left/Right) which lasted for 3 seconds before reverting back to the blank screen.

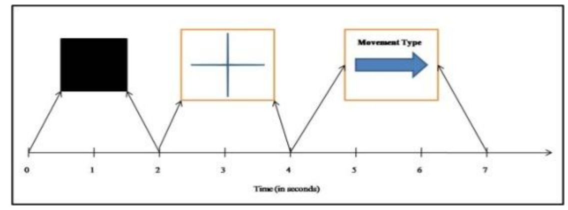

Figure 2: Timing schematic of the stimulus used in the experiment.

Therefore, each trial lasted for 7 seconds. Hence, the total data set for each session comprised of $1750 \times 3 \times 30$ data. The training and testing data were chosen randomly to avert any systematic feedback. Sensorimotor rhythms occurring in the frequency band: 8-30 Hz was filtered using a digital IIR bandpass filter of order 14.

3. Feature Extraction

3.1. Correlation Dimension

Fractal nature may arise from the criticality of a self-organized system. Self-regulating complex systems of the human body are the primary generators of biopotentials. Linear spectral methods do not have the flexibility to detect cumulative phase properties of nonlinear signals which is its characteristic feature. These phase properties are generated from the coupling processes of different modes, which in turn lead to nonrandom phase structure.

Correlation Dimension is one of those measures which help us determine the attractor dimension in the state space. The evaluation of Correlation Dimension incorporates a long time trajectory in the state space, where points are laid on a spherical orbit of radius *r*, and then the Euclidean distance is calculated between each pair of points. Grassberger and Proccacia defined the correlation function through the following equation [7]:

$$C(r) = \lim_{n\to\infty} \frac{1}{N(N-1)} \sum_i \sum_j s\left(r - |x_i - x_j|\right)$$

$$such\ that\ (i \neq j) \qquad (1)$$

where, $|x_i - x_j|$ is the Euclidean distance between the points x_i and x_j of the spherical orbit and *s* is the unit step function. For a lot of attractors, this *C(r)* exhibits a power law dependence on *r*, as $r \to 0$; that is

$$\lim_{r\to 0} C(r) = ar^d \qquad (2)$$

Based on this relationship, the following expression defines the Correlation Dimension:

$$d_c = \lim_{r\to 0} \frac{\ln C(r)}{\ln r} \qquad (3)$$

The dimension *d* is always a fraction in the case of chaotic attractors.

3.2. Higuchi Fractal Dimension

Any curve which is fractal in nature can be subdivided into *k* similar curves ($k = k_1, k_2 \dots k_{max}$). The length of this curve is proportional to k^{-D} , where fractal dimension (D) determine the complexity of the curve. A simple curve will have *D* equal 1, while for a curve which nearly fills out the plane, *D* is close to 2. [4]

Construction of phase space and data embedding are not necessary for calculating the fractal dimension by Higuchi's method. [5, 6, 24] The algorithm computes a new time series y_m^k based on a given finite time series:

$y = \{y(1), y(2) \dots, y(N)\}$, by the following equation:

$$y_m^k = \left[y(m), y(m+k), \dots, y\left(m + \left[\frac{N-m}{k}\right]\right).k\right] \tag{4}$$

for $m = 1, 2, \dots, k_{max} = 8$

Both *m* and *k* are integers which indicate the initial time and the time interval respectively. The length, $L_m(k)$ of each curve is calculated as

$$L_m(k) = \frac{1}{k}\left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} y(m+ik) - y(m+(i-1)k)\right)\frac{N-1}{\left[\frac{N-m}{k}\right]k} \tag{5}$$

The Fractal Dimension thus is computed by:

$$D = \left[\frac{\log_2(L_m(k))}{\log_2 k}\right] \tag{6}$$

4. Feature Classification Using Kernelized Support Vector Machines

The primary idea revolves around the formation of an optimal hyperplane which perfectly separates multi-dimensional data into binary or multiple classes. In some cases the data is not easily separable using linear methods, in this situation SVM plays a significant role by introducing the concept of "kernel induced feature space". In this concept, the data to be analyzed or classified is extended to a higher dimensional space which makes it easily separable Support vector machines belong to the category of kernel based classification methods which possess some innate advantages, like:

- Its ability to generate non-linear decision boundaries using linear classification methods.
- The application of kernel functions which enables users to use it on the data which has no fixed dimensional vector space representation.

SVM training always tries to find the global minimum and its performance depends on the type of kernel selected, where the error penalty parameter is user-defined. [13, 14, 15] SVM gained popularity primarily because of its promising features like better empirical performance. The formulation based on Structural Risk Minimization (SRM) principle, was shown to be superior to Empirical Risk Minimization (ERM) principle used in conventional neural networks. SRM minimizes the upper bound on the expected risk, while ERM minimized the error on the training data.

For a binary classification problem, if the training data is labelled as $\{x_i, y_i\}, i = 1, \dots, l, y_i \in \{+1, -1\}, x_i \in R^d$. Suppose there is a hyperplane which separates the two classes ("*the separating hyperplane*"). The point x which lie on the hyperplane satisfies the equation $w.x + b = 0$, where w is normal to the hyperplane. $|b|/_{\|w\|}$ is the perpendicular distance between the hyperplane to the origin, and $\|w\|$ is the Euclidean norm of w. Let, d^+& d^- be the shortest distance from the hyperplane to the nearest positive or negative examples respectively. The margin of the generated hyperplane would be defined as $[d^+ + d^-]$. The primary aim of any type of SVM is to find the hyperplane with the largest margin. If we assume that all training data satisfy the following constraints:

$$x_i.w + b \geq +1, for\ y_i = +1 \tag{7}$$

$$x_i.w + b \leq -1, for\ y_i = -1 \tag{8}$$

These equations can be combined to form the resulting equation as follows:

$$y_i(x_i.w + b) - 1 \leq 0, \forall\ i \tag{9}$$

If the vectors are distributed non-linearly, then it becomes essential to use a kernel function to map the data into a higher dimensional hyperspace wherein a multi-dimensional hyperplane can be used to segregate the data. Kernel functions correspond to an inner product in some expanded hyperspace. Mercer's Theorem states that every semi-positive definite symmetric function is a kernel. The dot product $K_{ij} \equiv K(x_i, x_j)$, represents Gram Matrix (a matrix of dot products in the Euclidean space). Prior to this process, each data point is mapped into the higher dimensional hyperspace via some transformation $\Phi: x \rightarrow \varphi(x)$. For kernalized SVM, the differentiating function would be of the form

$$f(x) = sign(\boldsymbol{w}.\phi(\boldsymbol{x}) + \boldsymbol{b}) \quad (10)$$

Kernel for the dot product in the higher dimensional feature space would be

$$K(x_a, x_b) = \phi(\boldsymbol{x_a}).\phi(\boldsymbol{x_b}) \quad (11)$$

The polynomial kernel function is given by:

$$K(x_i, x_j) = (\boldsymbol{x_i}.\boldsymbol{x_j} + \boldsymbol{1})^p \quad (12)$$

where, p is a tunable parameter. Firstly, a linear kernel

$$K(x_a, x_b) = (\boldsymbol{x_a}.\boldsymbol{x_b} + \boldsymbol{1}) \quad (13)$$

Secondly, a quadratic kernel

$$K(x_a, x_b) = (\boldsymbol{x_a}.\boldsymbol{x_b} + \boldsymbol{1})^2 \quad (14)$$

Finally, a polynomial kernel of order 3 (Cubic kernel)

$$K(x_a, x_b) = (\boldsymbol{x_a}.\boldsymbol{x_b} + \boldsymbol{1})^3 \quad (15)$$

In this paper we compare the performance of the polynomial kernel in classification of Left/Right limb using partial limb movement imagery (i.e. finger, distal portion of the limb, proximal portion of the limb). In order to find the tendency of the complexity pattern we tested the data recorded in the final day (9^{th} day of the experiment) with all the previous recordings we had obtained in the earlier 8 days of the experiment. The SVM's were trained distinctly with the data obtained previous 8 days pertaining to each session, with the aim of testing the data obtained in the 9^{th} day. The resulting performance of the classifier would give us the probability of correct classification for those particular sessions while the classifier is trained using the data obtained at a prior date. [24]

4.1. Performance of the classifier

The performance of a classifier is generally measured by its mean probability of correct classification over all trials. However, it may not be the actual measure of its accuracy as the accuracy varies with the training set. In this paper we present a novel Sugeno-type fuzzy inference system (SFIS) which measures the performance not only by averaging its performance over all trials but also takes into consideration, the performance of the classifier for each individual trial.

For any two inputs, $x_1 and\ x_2$ the Sugeno-type FIS returns an output: $z = ax_1 + bx_2 + c$.

Four membership functions were defined corresponding to a level of accuracy achieved (individual or averaged):

a. ***Poor:*** Sigmoid function with parameters [-240 0.80]
b. ***Average:*** Gaussian function with parameters [0.05 0.85]
c. ***Good:*** Sigmoid function with parameters [240 0.90]
d. ***Excellent:*** Sigmoid function with parameters [240 0.98]

The rule base of the FIS consisted of six rules:

i. $IF\ (\boldsymbol{Individual\ Accuracy})\ or\ (\boldsymbol{Average\ Accuracy}) \in \boldsymbol{Poor}\ THEN\ \boldsymbol{Movement\ type\ Accuracy} \equiv \boldsymbol{C_{poor}}$
ii. $IF\ (\boldsymbol{Individual\ Accuracy})\ or\ (\boldsymbol{Average\ Accuracy}) \in \boldsymbol{Average}\ THEN\ \boldsymbol{Movement\ type\ Accuracy} \equiv \boldsymbol{C_{average}}$
iii. $IF\ (\boldsymbol{Individual\ Accuracy})or\ (\boldsymbol{Average\ Accuracy}) \in \boldsymbol{Good}\ THEN\ \boldsymbol{Movement\ type\ Accuracy} \equiv \boldsymbol{C_{good}}$
iv. $IF\ (\boldsymbol{Individual\ Accuracy})\ or\ (\boldsymbol{Average\ Accuracy}) \in \boldsymbol{Excellent}\ THEN\ \boldsymbol{Movement\ type\ Accuracy} \equiv \boldsymbol{C_{excellent}}$
v. $IF\ (\boldsymbol{Individual\ Accuracy}) \notin \boldsymbol{Poor}\ THEN\ \boldsymbol{Movement\ type\ Accuracy} = \boldsymbol{Individual\ Accuracy}$
vi. $IF\ (\boldsymbol{Average\ Accuracy}) \notin \boldsymbol{Poor}\ THEN\ \boldsymbol{Movement\ type\ Accuracy} = \boldsymbol{Average\ Accuracy}$

The output level z_i for each rule is weighted by the firing strength of the rule, which is given by:

$$w_i = probor(\mu_{x_1}, \mu_{x_2}) \quad (16)$$

where, $probor$ represents probabilistic OR and μ_{x_1} and μ_{x_2} are the membership functions of x_1 and x_2 respectively. Final output is the weighted average of all the N outputs, computed as

$$Final\ Output = \frac{1}{T}\sum_{trial=1}^{T} \frac{\sum_{i=1}^{N} w_i x_i}{\sum_{i=1}^{N} w_i} \quad (17)$$

$where, T = total\ number\ of\ trials\ undertaken$

5. Experimental Results And Analysis

The following table shows the changes of correlation dimension and fractal dimension at the beginning and end of each phase of the experiment:

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TABLE 1: Categorization of Correlation Dimension measures at the beginning and end of each phase per session.

	Correlation Dimension											
	Finger Movement Imagery				Distal Limb Movement Imagery				Proximal Limb Movement Imagery			
	Right Arm		Left Arm		Right Arm		Left Arm		Right Arm		Left Arm	
	Start	End	Start	End	Start	End	Start	End	Start	End	Start	End
Phase 1	0.98401	0.98278	0.98695	0.9852	0.98323	0.98392	0.98393	0.98621	0.98296	0.98878	0.98703	0.98565
Phase 2	0.9907	0.97981	0.98464	0.9901	0.98019	0.98726	0.98531	0.98833	0.98224	0.99138	0.98452	0.991
Phase 3	0.98476	0.98219	0.98719	0.9827	0.98819	0.98145	0.98447	0.98042	0.98778	0.98152	0.98566	0.98323

TABLE 2: Categorization of Fractal Dimension measures at the beginning and end of each phase of every session.

	Higuchi Fractal Dimension											
	Finger Movement Imagery				Distal Limb Movement Imagery				Proximal Limb Movement Imagery			
	Right Arm		Left Arm		Right Arm		Left Arm		Right Arm		Left Arm	
	Start	End	Start	End	Start	End	Start	End	Start	End	Start	End
Phase 1	1.2479	1.2461	1.2485	1.2493	1.2527	1.2438	1.2523	1.2433	1.1773	1.2224	1.1697	1.2189
Phase 2	1.2461	1.2308	1.2493	1.2311	1.2438	1.2271	1.2433	1.2261	1.2224	1.2248	1.2189	1.2264
Phase 3	1.2271	1.2461	1.2274	1.2465	1.2233	1.2251	1.2214	1.2348	1.2312	1.2337	1.2307	1.2338

Classification Performance Analysis

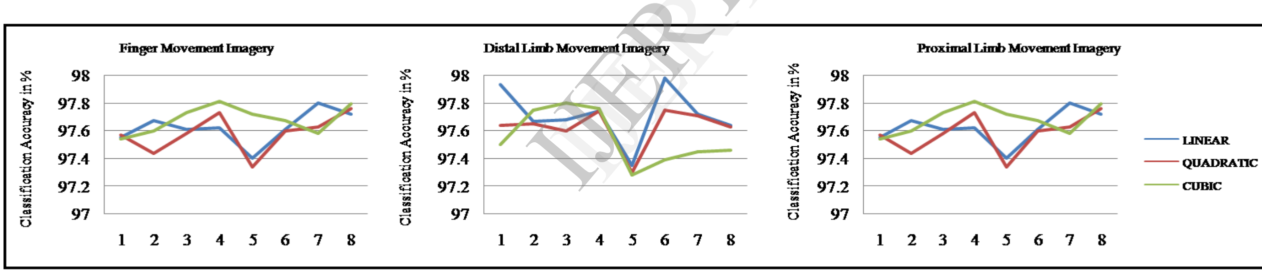

Fig. 3: Fluctuations of Classification accuracy of polynomial SVM during temporal evolution based on Correlation Dimension Measures

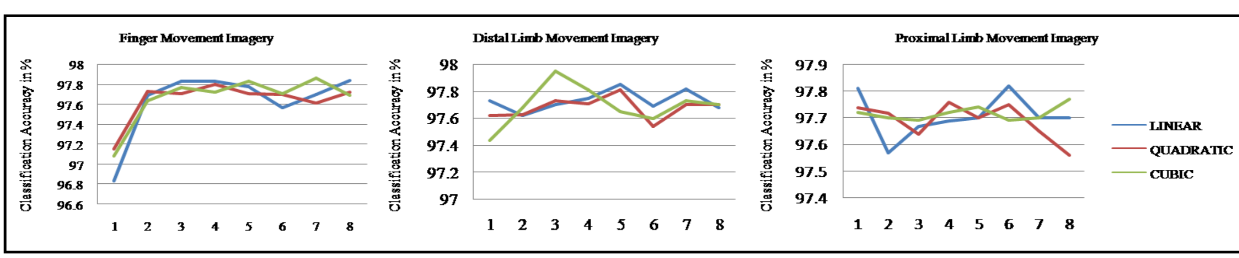

Figure 4: Fluctuations of Classification performance of polynomial SVM during temporal evolution based on Fractal Dimension measures.

All the classifiers were consistently accurate with 97% accuracy except for one case where the classifier accuracy was 96.81% (training by 1st day 1st session using correlation dimension feature). The classification of each session took less than 1 second to compute. The linear kernel had the fastest computation as compared to the quadratic and the cubic kernel with a mean of 1.5121 s, and a standard deviation of 0.1091.

6. Discussion

We know that as we do mental practice of new movement forms, new sensorimotor programs are generated, or the older movement related sensorimotor programs get modified. From this experiment it is visible that as the mental practice for the imagery is repeated the new imagery forms a linear or polynomial relationship with the older imagery [24]. The classification performance of the Finger movement imagery using fractal dimension shows that the imagery of the final day of phase 3 (Index: 9) forms a linear relationship with the imagery taken the previous day (Index 8), while it forms a polynomial relationship with the imagery taken in the first day (Index 1). During the experiment, it was seen that the fractal dimension of the C3 electrode was always distinctly higher than that of C4 in each day of the experiment, thereby confirming that the contra-lateral portion of the brain is activated during the imagination of the bodily actions. It can also be seen that the dimension of the chaotic attractor of the EEG sequence observed on the final day is related to its preceding day imagery more accurately by a polynomial function while it relates to the attractor of an imagery taken two weeks prior by a quadratic function.

Distal Limb Movement Imagery classification analysis portrays the fact that during the intermediate stages of the experiment, both the fractal dimension and the correlation dimension have a cubic relationship with the data obtained in the final day of the experiment. It may be a result of the modifications of the central sensorimotor programs corresponding to the distal limb movement imagery.

The proximal limb movement imagery classification analysis also showed distinct patterns which manifest due to the temporal evolution of the Fractal dimension and Correlation dimension parameters. The data obtained from these sessions showed a unique trend of having a cubic relationship with the data obtained in the recent past, while it has a linear relationship with the data obtained in the distant past.

7. Conclusion

This type of analysis using the temporal evolution of the fractional dimension parameters would help us in calibrating the control signals of the neuroprosthetic arm. Moreover, the performance analysis using the Sugeno-type FIS would not only provide us with the classification accuracy averaged over time but would also help us to evaluate the performance on the basis of the fluctuations that are a result of the individual trial characteristic. The computation time of the linear kernel SVM was comparatively lower than that of the quadratic and cubic kernel SVM.

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