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SPECIAL ISSUE ON RECENT RESEARCH CHALLENGES IN BIO-MEDICAL APPLICATIONS

Optimizing Support Vector Machine for Electrocorticography Based Brain Computer Interface Using Clonal Selection

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Cognitive neuroscience and brain imaging technologies advances has enableddevices to interface directly with the human brain. This is possible through use of sensors that capture signals in the brain, corresponding to certain thought forms. Braincomputer Interface's (BCI) central element, is a translation algorithm converting electrophysiological input from user into output capable of controlling external devices. This study presents a BCI system which pre-processes and extracts features from Electrocorticography (ECoG) signals using Symlet Wavelets. Signals are classified using Support Vector Machine (SVM) with Radial Basis Function (RBF). It is proposed to optimize the C and Gamma parameters of the RBF kernel using Clonal Selection Algorithm (CLONALG) in this study.

Key words: Brain Computer Interfaces (BCIs), Electrocorticography (ECoG), Symlet Wavelets, Support Vector Machine (SVM), Radial Basis Function (RBF), Clonal Selection Algorithm (CLONALG).

A BrainComputer Interface (BCI) is a hardware that allows humans to interact with a computer through brainwaves. Presently, BCI is used for healthcare, and education based on neural-feedback which is a type of brainwave using bio-feedback. BCI controls computers using human brain waves. BCIs convert brain signals into outputs communicating user's intent[1]. As this new communication channel is independent of peripheral nerves and muscles, it is resorted to by those with severe motor disabilities.

BCIs use invasive and non-invasive methods. Electroencephalographic activity (EEG)[2] from the scalp is used by non-invasive BCIs. Though convenient, safe and inexpensive, they are susceptible to artifacts like electromyography (EMG) signals, which have low spatial resolution and so need much user training. Single-neuron activity recorded in the brain is used by invasive BCIs. Though having higher spatial resolution and providing control signals with much freedom, BCIs still are dependent on electrodes in the cortex and so have problems ensuring stable long-term recordings.

Electrocorticography (ECoG) is acute recording of electrical activity directly from cortical surface during exposure in surgical treatment of epilepsy[3, 4]. Recent studies emphasized the intraoperative ECoG importance for precise epileptic focus localization and good surgical outcome. ECoG is not invasive, as neuronal recordings as the brain is not entered into. It has a higher Signal-to-Noise Ratio (SNR) than EEG and also higher spectral/spatial resolution[5] which necessitates re-engineering of signal processing and classification techniques found in conventional EEG-based BCIs. Extreme data scarcity due to limited time available for volunteering patients is an obstacle to characterize information in ECoG signals.

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Feature Extraction creates features by decomposing original data. A feature is a combination of attributes that captures important data characteristics. The feature becomes a new attribute. Feature extraction allows data description with limited attributes than original set[6]. It is useful to project n dimensions (attributes) to 2 or 3 dimensions for visualization. Some feature extraction applications are data compression, latent semantic analysis, pattern recognition, data decomposition, and projection. Feature extraction enhances supervised learning speed and effectiveness[7].

The features extracted are classified using Support Vector Machine with Radial Basis Function (SVM-RBF) kernel in this study. The advantages of using SVM for classification are that it has a regularization parameter, which avoids over-fitting. SVM uses the kernel trick so that knowledge about the problem can be built into the kernel. Local minima problem is avoided as a convex optimizationis utilized[8]. To improve the efficiency of the RBF kernel, the regularization parameter C and gamma is optimized. In this work, the RBF kernel is optimized using CLONALG. The Clonal Selection Algorithm, first called CSA and renamed CLONALG aims to develop an antibodies memory pool representing a solution to engineering problems. The algorithm provides two mechanisms to search for desired final pool of memory antibodies. CLONALG is a system inspired by acquired immunity clonal selection theory which was successful on varied engineering problem domains.

Related Work

Various studies related to feature extraction, feature reduction, channel selection, classification of signals for BCI is available in the literature. Some of the works are reviewed in this section. An experimental paradigm combining anodaltranscranialDirect Current Stimulation (tDCS) with a Motor Imagery (MI)-based feedback EEG BCI system was designed by Wei, *et al*.,[9]. Results revealed that anodal tDCS induced SensoriMotorRhythm (SMR)-related Event-Related Desynchronization(ERD) pattern changes in upper-mu (10-14 Hz) and beta (14-26 Hz) rhythm components. An approach to image cortical rhythmic modulation connected to motor imagery using Minimum-Norm Estimates in Frequency Domain (MNEFD) was developed by Yuan, *et al*.,[10]. Statistical source analysis showed that movement imagination coupled with maximum correlation was localized in sensorimotor cortex. A cross-validation state-space framework based method was introduced by Cheung, *et al*.,[11] to compare various cortical interaction models fidelity to measure scalp EEG or Magnetoencephalography (MEG) data being modeled.

A 6.4 ì W ECoG/EEG Processing Integrated Circuit (EPIC) with 0.46 ìVrmis noise floor meant for emerging BCI applications was presented by Zhang, *et al*.,[12]. Measured results from in vivo ECoG recording from an awake monkey's primary motor cortex were presented.Schalk and Leuthard[13] provided ECoG's general perspectives; describeddifferent electrophysiological features detected by ECoG; elaborated signal acquisition issues, protocols, and online ECoG- based BCI studies performance to date; they presented current ECoG studies important limitations; discussed opportunities for more research; and finally revealed ideas for later clinical implementation.

Discrete wavelet transform method was used by Liu, *et al*.,[14] to decompose average power of channel C3/C4 and P3/P4 in left/right hands imagined movement during experiments time. Zhao, *et al*.,[15] combined wavelet entropy and band powers for BCI systems feature extraction based on imaginary left/right hand movements. The new algorithm was applied on BCI competition 2003's data set III with good results. An improved feature extraction, MultivariateAdaptive Autoregressive (MVAAR) models based method for non-stationary nature of EEG data was proposed by Wang, *et al*.,[16]. This necessitated some adaptation of BCI systems. Feature extraction methods between MVAAR and others were compared. The result revealed that MVAAR was effective for online BCI system feature extraction.Dumitru and Datcu[17] suggested studying dependence of information extraction technique performance on Synthetic Aperture Radar (SAR) imaging parameters. The products invariance with orbit direction and incidence angle was investigated.Two new contributions were proposed by Dópido, *et al*.,[18]. A new unmixing-based feature extraction technique was first developed. Second, they conducted a quantitative andcomparative assessment of unmixing-based feature extraction versus traditional methods with regard to hyper spectral image classification.A Bayesian framework for discriminative feature extraction for motor imagery classification in EEG-based BCI was proposed by Suk and Lee[19] where class-discriminative frequency bands and corresponding spatial filters were optimized by probabilistic and information-theoretic approaches. The proposed method's feasibility and effectiveness were demonstrated by analyzing results and success on three public databases.

A feature extraction method for motor imagery BCI using electroencephalogram was proposed byZhang, *et al*.,[20] which compared two existing methods on real data: a BCI Competition IV dataset and authors data from seven human subjects. The results proved the superior performance of motor imagery classification method producing higher classification accuracy with statistical significance (e"95% confidence level) in many cases.Park, *et al*.,[21] investigated efficiency of multivariate extensions of empirical mode decomposition (MEMD) in motor imagery BCI revealing that direct multichannel processing through MEMD ensured enhanced localization of EEG frequency information while its noise-assisted operation (NA-MEMD) provided localized time-frequency representation.Zhang, *et al*.,[22] suggested and studied a Bayesian analysis theory for spatial filtering regarding Bayes error. Following maximum entropy, a gamma probability model was introduced to describe single-trial EEG power features. Results showed that Bayes error could be reduced through application of a new spatial filter having reduced Rayleigh quotient.Lotte, *et al*., [23] presented a trainable feature extraction algorithm FuRIA for noninvasive BCI. FuRIA evaluations showed that extracted features were interpretable and could provide high classification accuracies.Coyle, *et al*.,[24] introduced many modifications to learning algorithm of Self-Organizing Fuzzy Neural Network (SOFNN) to improve computational efficiency. Results indicate that a general NTSPP parameters set chosen through SA provides best results when tested in a BCI system.

A new approach to tackle signal variability through focus on time recurrent learning subspaces was proposed by Gowreesunker, *et al*.,[25]. The authors introduced two methods to use learned subspaces in movement direction decoding and showed decoding power improvement from 76% to 88% for an unstable subject. Decoding was consistent across subjects.Das, *et al*.,[26] identified four mental states decoding from six epileptic patients ECoGs engaged in a memory reach task. A novel signal analysis technique was applied to high-dimensional, statistically sparse ECoGs recorded by many electrodes. The new technique offered a systematic analysis of brain information processing spatio-temporal aspects. Khan and Sepulveda[27] showed that spatial filtering in multichannel EEG effectively extracted discriminant information from single-trial EEG for left/right wrist movement imagery. Average recognition rate of around 89% was achieved in all four movements (flexion, extension, supination, and pronation) between left/right wrists in five healthy subjects. The results were comparable to highest rates in literature.

An empirical Bayesian Linear Discriminant Analysis (BLDA), where neurophysiological and experimental priors were considered simultaneously was proposed by Lei, *et al*.,[28]. Feature selection was weighted differently, and classification performed jointly. Results confirmed BLDA's superiority in accuracy and robustness to LDA, regularized LDA, and SVM.An algorithm, S-dFasArt, to classify spontaneous mental activities from EEG signals was proposed byCano-Izquierdo, *et al*.,[29] to operate a noninvasive BCI. The results were compared with other published methods and improved on their success rates.

A general framework that defined a set of classification algorithms for BCI was proposed by Gianfelici and Farina[30] which validated classification of single-trial EEG signals recorded during motor imagination. This was compared to two additional standard datasets from BCI competition and with other feature extraction and classification techniques. The proposed framework suited a broad number of BCI applications.A hybrid algorithm to improve classification success rate of MI-based EEG signals in BCIs was proposed by Siulyand Li[31]. Experimental results on two datasets showed that it provided improvement compared to logistic regression and kernel logistic regression classifiers. Results indicated that the new approach outperformed achieving 7.40% improvement over the other eight studies best results.Shenoy, *et al.*,[32] examined classifiability of ECoG for use in a human BCI. The results revealed that some spectral features could be used across many subjects to classify different movements accurately. An average two-class classification accuracy of 95% for real movement and 80% for imagined movement was seen.

METHODOLOGY

Dataset

Dataset used for evaluating the suggested method is Data Set I for BCI Competition III with motor imagery in ECoG recordings. A subject performed imagined movements of left small finger or tongue in a BCI experiment. The trails picked up electrical brain activity's time series. The recordings had a 1000Hz sampling rate. After amplification recorded potentials were stored as microvolt values. Each trial had an imagined tongue/imagined finger movement recorded for 3 seconds. To prevent data reflecting visually evoked potentials, recording started 0.5 seconds after the conclusion of visual round. Training data was brain activity for 278 trials and similar activity for100 trials was test data[33].

Symlet Wavelet

A time and frequency bounded waveform is a wavelet. Fourier analysis includes breaking a signal into varied frequency sine waves. Similarly, wavelet analysis breaks up a signal into shifted/ scaled versions of original/mother wavelet. Symlets are nearly symmetrical wavelets proposed by Daubechies to modify the db family and have the properties of both wavelet families[34]. Symlets - compactly supported wavelets have least asymmetry and highest vanishing moments for specific support width.

Symlet wavelets are a wavelets family. They are modified Daubechies wavelet with increased symmetry[35]. Properties of both wavelet families are similar. They have 7 different Symlet functions from sym2 to sym8. In symN, N is the order. The wavelet which is efficient in denoising applications is Symlet wavelet family. Symlet wavelets in practice are also selected even number of wavelets as Daubechies[36]. Symlets, when applied to signal, perform better, and SNR of reconstructed/

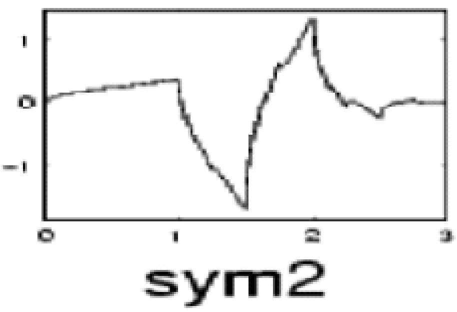

Fig. 1. Sym2 Wavelet Function Waveform

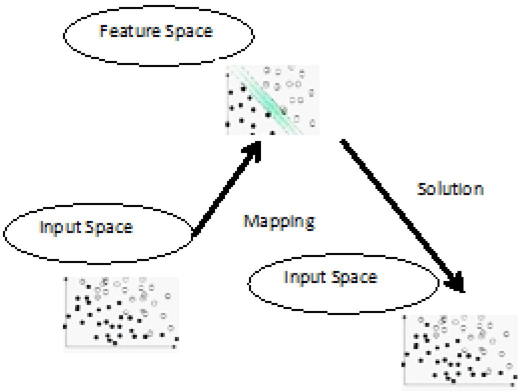

Fig. 2. SVM Process Flow

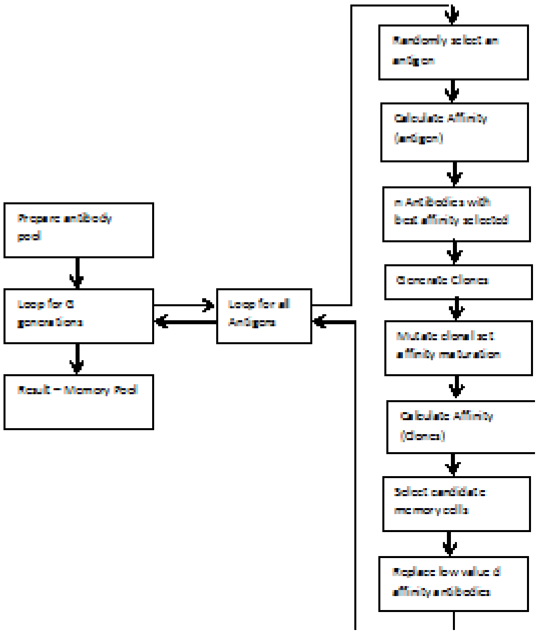

Fig. 3. Overview of the CLONALG algorithm

denoised signal improves. Sym6 suits hard thresholding. When additive white Gaussian 10 db noise is added to signal, it covers the whole signal spectrum and hence it is hard to remove. But, observing noisy signal's coefficients and application of proper thresholds, noise can be deleted.

Support Vector Machine (SVM)

SVMs are a large-margin, and not probabilistic classifiers[37]. The idea behind training procedure in the two-category case is to locate a maximum margin hyperplane, represented by vector w, that separates feature vectors in one class from those of the otherand which has a large separation or margin.

One way to perform binary classification is by constructing a hyperplane described byweight vector w and bias term b, based on an examples training set with data vectors x_i and corresponding class labels y_i[38],

$$(x_1, y_1)\ldots(x_l, y_l) \in R^N \times \{-1,1\} \quad \ldots(1)$$

A machine-learning algorithm should find such a hyperplane according to suitable optimality criterion. The class label of new data vector x can be predicted by it on weight vector w in the tests phase.

$$f(x) = w \cdot x + b \quad \ldots(2)$$

An aspect of the SVM model is that data enters as dot pairs product leading to the second problem stated above being resolved. SVMs idea is to map training data into a higher dimensional feature space through mapping ö(x) and by constructing a separating hyperplanethere with maximum margin yielding a non-linear decision boundary in original input space. Use of kernel function, K(x, z) = hö(x), ö(z)i, computes separating hyperplane without carrying outmapping in feature space[37].

$$\text{RBF Kernel: } K(x,z) = \exp\left(\frac{-\|x-z\|^2}{2\sigma^2}\right) \quad \ldots(3)$$

Kernel selection is crucial for SVM training and classification. A well designed kernel function minimizes generalization error, increases prediction accuracy, and also accelerates convergence speed. Two common optimization methods are addition of parameters and kernel

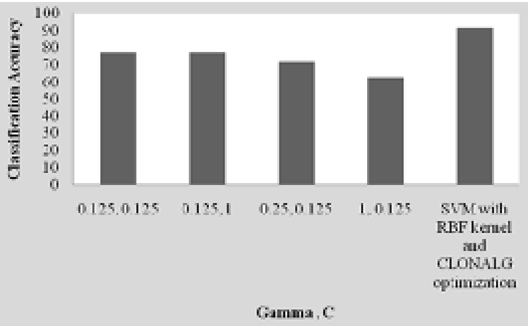

Fig. 4. Classification Accuracy

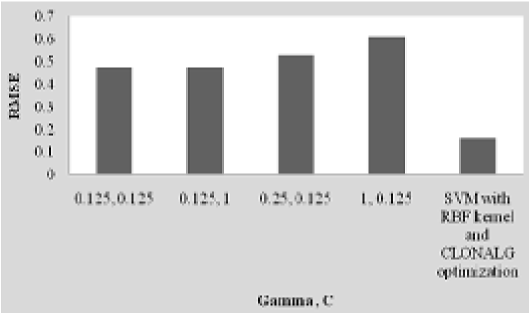

Fig. 5. RMSE

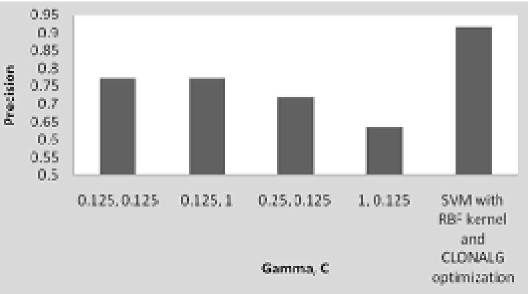

Fig. 6. Precision

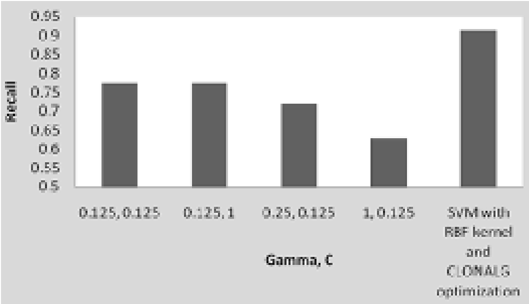

Fig. 7. Recall

alignment[8]. Additional parameters in the kernel are optimized to improve the performance. For the RBF kernel,common strategy is to optimizethe**sigma** parameter with the C parameter. Kernels such as the polynomial or sigmoid[8] kernels can also be optimized in a similar fashion.

To design an eûicient SVM-RBF model, RBF regularization parameter C and Gamma parameters values have to be selected carefully. The regularization parameter C determines the tradeoû cost between minimizing training error and minimizing model complexity.The Gamma parameter deûnes non-linear mapping from input space to a high-dimensional feature space

CLONALG

Clonal selection theory inspired artificial immune system technique is CLONALG (CLONal selection ALGorithm). CLONALG has two populations: one of antigens, Ag, and another of antibodies, Ab (denoted byP(t)) [39]. Individual antibody/antigen are represented by string attributes $m = m_L \ldots m_1$, i.e., a point in an L—dimensional shape space S, m "S^L. The Ab population is a set of current candidate solutions, with Ag being the environment needing recognition. After random initialization of first population $P^{(0)}$ the algorithm loops for a predefined maximum generations (N_{gen}).

The following provides an overview of the steps of the CLONALG algorithm.

1. Initialization
2. Loop
i. Select Antigen
ii. Exposure
iii. Selection
iv. Cloning
v. Affinity Maturation (mutation)
vi. Clone Exposure
vii. Candidature
b. Replacement
Finish

The algorithm generates a random cells population and computes their fitness related to the issue on hand. The iterative process starts by constructing a sub-population Ab_n of size n, composed by n best antibodies of the cells population[41]. A new clone's population C is built by generating C clones of each element on Ab_n. CLONALG's standard parameters are: ñ, C, n and A. CLONALG works with antibodies set: A population of C clones. This parameter's value is

CLONALG's pseudo code for optimization [40] is as follows:

Input: Ab, Ngen, n, d, L, β

Output: Ab, f

1. for t=1 to Ngen
    1.1 f:= decode(Ab);
    1.2 $Ab_n := select(Ab, f, n)$;
    1.3 C:=clone(Ab_n, β, f);
    1.4 $C^* := hypermut(C, f)$;
    1.5 $f^* := decode(C^*)$;
    1.6 $Ab_n := select(C^*, f^*, n)$;
    1.7 Ab:=insert(Ab,Ab_n);
    1.8 Ab_d := generate(d,L); Randomly generate s antibodies of length L
    1.9 Ab:=replace (Ab,Ab_d, f);

end

2. f:=decode (Ab); Function decode should decode and evaluate the decoded values.

controlled to guide a trade-off between the algorithm's intensification and diversification processes.

To establish an efficient Support Vector Machine (SVM) two parameters such as C and r are predetermined carefully. Therefore, the purpose of this investigation is to develop a SVM model with CLONALG's optimization that can automatically determine the optimal parameters, C and r, of SVM with the highest predictive accuracy and generalization ability simultaneously.

The basic idea in sketching a non-linear SVM model isto map the input vector $x \in \Re^n$ into vectors z of a higher-dimensional feature space $F(z = \varphi(x))$, where denotes the mapping , and to solve a linear classification problem in this feature space

$$x \in \Re^n \to z(x) = [a_1\varphi_1(x), a_2\varphi_2(x), ..., a_n\varphi_n(x)]^T \in \Re^f \quad ...(4)$$

Mercer kernel can be approximated by $k(x, y) = \varphi(x)^T \varphi(y)$, which performs the non-linear mapping.

RESULTS AND DISCUSSION

Experiments were conducted using 278 numbers of instances from the dataset. Features were extracted using Symlet wavelet. 193 attributes were used to classify the instances. All the experiments were conducted for 10-fold cross validation. Table 1 and 2 shows the gamma and C values for classification accuracy, RMSE, Precision

Table 1. Classification Accuracy and RMSE for varying Gamma and C value

SVM RBF Parameters Gamma, C	Classification Accuracy %	RMSE
0.125, 0.125	77.3381	0.476
0.125, 1	77.3381	0.476
0.25, 0.125	71.9424	0.5297
1, 0.125	62.9496	0.6087
SVM with RBF kernel and CLONALG optimization	91.37	0.1621

Table 2. Precision and Recall

SVM RBF Parameters Gamma, C	Precision	Recall
$\Re^n \to \Re^f$ 0.125, 0.125	0.773	0.773
0.125, 1	0.773	0.773
0.25, 0.125	0.72	0.719
1, 0.125	0.635	0.629
SVM with RBF kernel and CLONALG optimization	0.9158	0.91365

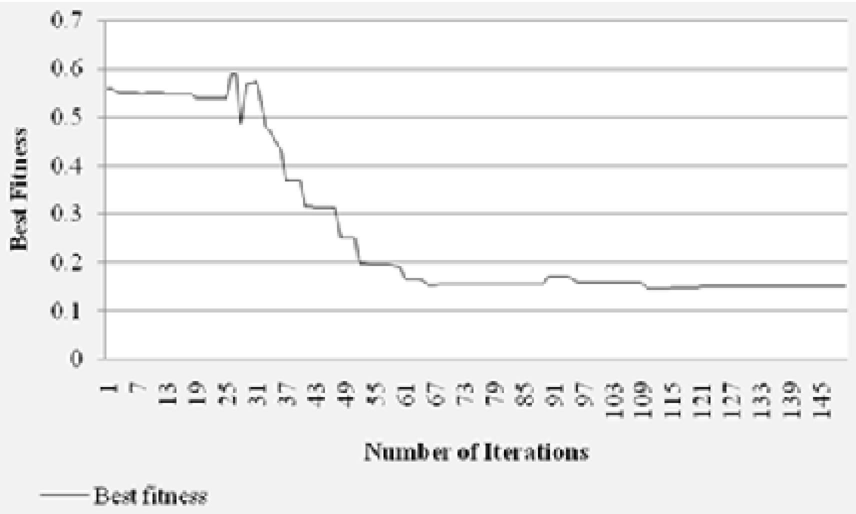

Fig. 8. Best Fitness

and recall respectively. Figure 4 to 7 shows the result graph for the same. Figure 8 shows the best fitness.

It is observed from the Table 1 that the varying of the parameter C has no effect on the classification accuracy or the RMSE. Also, higher value of Gamma leads to inefficient performance of the SVM. Figure 4 shows theclassification accuracy, it is observed that the proposed approach achieves better performance than SVM Gamma value 1in percentage of 18.14% and the proposed approach having lesser RMSE value than SVM Gamma value 1in percentage of 65.95%.

Similar to the classification accuracy, precision and recall are high when Gamma value is 0.125. Further investigations are required to improve the classification of the ECoG signals. The figure precision and recall shows that the proposed approach was given the better performance than SVM Gamma value 1 by 18.47% and by 18.2% for recall.

From figure 8 it is observed that the convergence occurred at iteration number 140.

CONCLUSION

ECoG includes a spatial scale between EEG and intra-cortical microelectrode recording, and ECoG offers a balance between invasiveness, spatiotemporal resolution, and signal stability for BCI applications. BCI is an exciting research area which one day will become reality of controlling computers through intelligent interfaces that are capable of interpreting users' commands directly from electrical brain signals. BCI has progressed, but it is slowed by many factors including noise in brain signals, muscular artefacts and inconsistency and variability of user attention/intentions.Signal classification uses SVM with RBF in this paper. CLONALG optimizes SVM. For intensification, the strategy works with many clones to improve. When improvement procedure was applied successfully, the algorithm increases clones number which follow improvement process in next iteration. Experiments were undertaken through tenfold cross validation and accuracy achieved is satisfactory but further work is needed for classification accuracy improvement.

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