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Optimizing Feature Selection and Support Vector Machine Using Clonal Selection for Brain Computer Interface

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Abstract: Brain computer Interface's (BCI) central element, is a translation algorithm converting electrophysiological input from user into output capable of controlling external devices. Studies in the past few years depict how humans and animals use brain signals to convey their intent to a computer using BCIs. This is possible through use of sensors that capture signals in the brain, corresponding to certain thought forms. Settings of kernel parameters setting in the SVM training process can impact accuracy in classification. The Clonal Selection Algorithm (CLONALG) is one such system inspired by the clonal selection theory of acquired immunity, which has shown success on broad range of engineering problem domains. Results show that the proposed approach displayed better performance in accuracy, recall, precision than SVM with RBF kernel and CLONALG optimization and CLONALG Feature selection and SVM with RBF kernel and CLONALG optimization by 3.85%, by 0.24% and by 0.02% respectively. Also the RMSE performs better by 19.15% for proposed approach.

Key words: Brain Computer Interfaces (BCIs) · Electrocorticography (EcoG) · Support Vector Machine (SVM) · Radial Basis Function (RBF) · Clonal Selection Algorithm (CLONALG)

INTRODUCTION

Brain–computer interfaces (BCI's), provide users the ability to control and communicate channels which have no dependence on typical channel outputs among peripheral muscles and nerves of the brain. Future hopes of converting this current BCI research into a augmentative and valuable communication technology, capable of assisting severe motor disabilities that prevent the usage of voluntarily muscle-controlled conventional augmentative technology. Electroencephalographic activities recorded from electrical brain activities. The focus is on brain electrical activity and from scalp the recording of electroencephalographic (EEG) is performed. As a new communication and control technology, recording can done inside the brain as single-unit activity [1].

BCIs can use non-invasive or invasive methods. Non-invasive BCIs use EEG activity to record on scalp which is convenient, safe and inexpensive. Though providing high benefits, it includes relatively low spatial resolution which is susceptible to Electromyographic (EMG) signals and requires extensive user training. In invasive BCIs, a single-neuron activity is used to record the brain's activity. BCI's provide greater spatial resolution, control signals but it depends on electrodes of cortex which face substantial problems to achieve stable long-term recordings. The small, high-impedance recording sites penetrates electrodes that are susceptible to signal degradation due to encapsulation [2].

Electrocorticography (ECoG) has recently gained attention as a recording technique for use in brain–computer interfaces. ECoG involves recording electrical signals from the surface of the human brain,

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typically in patients being monitored prior to surgery. ECoG is less invasive than neuronal recordings because the brain is unpenetrated and has higher Signal-to-Noise Ratio (SNR) than EEG with higher spectral and spatial resolution. This higher resolution necessitates re-engineering of the signal processing and classification techniques used in traditional EEG-based BCIs [3]. Compared to signals acquired from the scalp EEG and intraparenchymal single neuronal recordings, ECoG recordings have characteristics that make them especially suited for basic neuroscience research and resulting translational opportunities [4].

Brain signals often overlap both time and space, arise from a finite set of brain activities which are mixed with other signals. Moreover, these signals are not stationary as it may be distorted through EMGs, EOGs (electrooculography) and other artifacts. It is essential to require low dimension feature vectors to reduce complexities in the feature extraction stage without losing out on relevant data. Thus, the classification stage indicates the important feature vectors the signals finds important.

It is essential to achieve adaptive pattern recognition with the purpose of selecting good set of traits important to decode original user's intent. Lastly, the stage of control and interface can translate classified signals into meaningful commands to be implemented in any connectable device, for example: a wheelchair or a computer.

A major difficulty faced is selecting relevant features from an array of possible features. The "Curse of Dimensionality" diminishes the desirability of extremely prolific feature vectors represented in algorithms in training (Refer to the subsequent title). Although, only a few number of possible features can grow exponentially, it is a characteristic of feature selections to attempt to manually examine every possible subsets of a feature. But it must be noted that possibility number makes an exhaustive search impractical for moderate number of features. To minimize the number of features and to maximize the classification performance, some efficient optimization algorithms are applied [5].

Feature selection are used to identify powerful predictive subset of fields within a database and reduce the number of fields present within the mining process. This is procured through extracting as much information as possible from a given data set while using the smallest number of features, save significant computation time and build models that generalize better for unseen data points. According to the choice of features used to represent patterns that are presented to a classifier affects several pattern classification aspects, including the accuracy of the learned classification algorithm, the time needed for learning a classification model, multiple examples required to assist the learning process and associated feature cost associated. Along with feature selection, proper parameters setting improves the Support Vector Machine (SVM) classification accuracy [6].

CLONALG models, usually involve the representation of a selected group of candidate antibodies, either dependent on affinity against matching antigen patterns or through evaluating cost function related patterns. The elected group of antibodies are subject to cloning affected through affinity and hypermutability of clones which are inversely proportionate to affinities of clones. The resultant clonal-set competes with the antibody population for membership in the next generation and low-affinity population members are replaced by randomly generated antibodies [7]. CLONALG is the abbreviation of the clonal algorithm and has been inspired by the following elements of the clonal selection theory [8]:

- Maintenance of a specific memory set
- Selection and cloning of most stimulated antibodies
- Death of non-stimulated antibodies
- Affinity maturation (mutation)
- Re-electing a group of clones based on affinity proportionateness with antigen
- Generation and maintenance of diversity

A mixture kernel function based on radial based and polynomial kernel was introduced and the parameters of this new kernel function were optimized. Their algorithm gives the better results than normal SVM in fault diagnosis. But it has some disadvantages. Firstly, their immune optimization method refers to crossover parameter. But original immune optimization algorithm (CLONALG) has no crossover operator. The objective function of the immune optimization method is calculated based on training of SVM [9]. Because of these properties, clonal selection converges faster than genetic algorithm and does not catch local minimum.

The performance of the SVM classifier is evaluated. Feature selection using CLONALG followed by SVM parameter optimization. Section 2 deals with literature work, in section 3 the methods used are explained, sections 4 deals with results and discuss results obtained and finally section 5 concludes the work.

Related Works: Rathipriya *et al*., [10] suggested a hybrid algorithm to advance the classification achievement rate of MI-based ECoG in BCIs. Identical feature SVM classifiers were restored to verify the effectiveness of a suggested classifier, through any extractable trait acquired from cross-correlated classification methods. A ten-fold cross validation method is utilized to access procedural performances. The authors furthermore consider the performance of the suggested procedure by comparing it with existing system.

Zhao *et al*., [11] proposed an innovative BCI system using ECoG methods as extracting important features are a crucial task which can significantly affect any classification result. The initial step requires the application of discrete wavelet transformations to ECoG signals jumping from one subject's hypothesized movements of either the tongue or left little finger. After pre-processing, relative wavelet energy of selected 8 channels were extracted and built 40 dimension feature vector. The final step classifies results according to the probabilistic neural network (PNN). The offline analysis results show that ECoG signals used in BCI design, with new ideas and methods for feature extraction, classification of imaginary movements in ECoG-based BCI research.

Yan *et al*., [12] proposed a pattern recognition algorithm using wavelet analysis and Fisher Linear Discriminant Analysis (FLDA) for a typical ECoG-based BCI system. Initially a feature extraction method in ECoG signal processing such as Wavelet Variance (WV) or Wavelet Packet Variance (WPV) was proposed by considering the band interlacing phenomenon in wavelet packet transform and final traits were classified within optimal intervals under FLDA results acquired from ECoG data. The results show that the max accuracy for test data was 92%, WV and WPV was considered as efficient features for ECoG.

Song *et al*., [13] used ECoG signal from human cortex to decode phonetic units during the perception of continuous speech. By exploring the wavelet time-frequency features, the authors selectively responded to a proposed set of Chinese phonemes based on its equivalent ECoG electrode response. These electrodes are further added to gamma and its higher powered levels in order to separate a specific set of phonemes into the required cluster. There is a large cluster of organizations which mostly coincide with the available categories determined phonologically based on articulating mannerisms and place. These findings were unified into a decoding framework of Chinese phonemes clusters. Using SVM classifier, we achieved consistent accuracies higher than chance level across five patients discriminating specific phonetic clusters, which suggested a promising direction of implementing a speech BCI.

Aydemir and Kayıkçıoğlu [14] proposed a motor based ECoG imagery algorithm for recording different sessions. Extracted feature vectors obtained with wavelet transform were classified by k nearest neighbor method. The proposed algorithm was applied to Data Set I of BCI competition 2005 and achieved a classification accuracy of 95% on test set.

Krusienski *et al*., [15] presented a preliminary analysis of the relationship between EEG and ECoG event-related potentials (ERPs) recorded from a single patient using a BCI speller. BCI spelling model tests are conducted on a patient prior to implanting the ECoG grid, through a highly regulated scalp-recorder EEG. The patient achieved a near perfect spelling accuracy using EEG and ECoG. An offline analysis of average ERPs was performed to assess how accurately the average EEG ERPs was predicted from the ECoG data. The initial results indicate that EEG ERPs was accurately estimated from proximal asynchronous ECoG data using simple linear spatial models.

Bai [16] presented comparative BCI system to study various feature selection methods in order to enhance classification efficiency. These are supported through pre-processed ECoG signals and features which are extracted through a Wavelet Packet Tree model. A few algorithms used to select important traits are portrayed by Genetic Algorithms (GA), Mutual Informations (MI formulas), Information Gaining techniques (IG). BCI Competition level III and also through Data Set I. These methods are consecutively used to evaluate methods under a ECoG recordings motor imagery. Results demonstrated that the feature selection improved the classification accuracy.

Li *et al*., [17] utilize a Power Spectral Density mechanism to select features for maximizing the capabilities of electrodes to its optimum level. Common spatial pattern (CSP) algorithm is used for feature extraction and the nonlinear classification of motor imagery with SVM. The classification accuracy rate of 83% is achieved on Data set I of BCI Competition III.

Wei and Tu [18] proposed a modern single-trial ECoG classification algorithm to be used during motor imagery. Optimal channel subsets are selected based on its genetic algorithms acquired from multi-channel ECoG recordings, then the power features were extracted by CSP and finally Fisher discriminant analysis (FDA) is used for classification. The algorithm was applied to Data set I of BCI Competition III and the classification accuracy of 90% is achieved on test set with only seven channels.

Bai *et al*., [19] investigated individual difference of Visual Evoked Potentials (VEPs) with cognition task, in which a feature selection and channel optimization strategy was developed for the VEPs based biometric identification system, where three different methods, including the Fisher Discriminant Ratio (FDR), GA techniques and possible Recursive Feature Elimination (RFE) methods will be employed. Results revealed the feasibility of VEPs based EEG to be used for biometric identification. The proposed optimization algorithm had the ability to improve accuracy in simplification and identification of the system. Future studies on the above technique will push forward a unique and novel idea to analyze individual differences in EEG.

Ding [20] proposed a new strategy combining with the SVM classifier for features selection that retains sufficient information for classification purpose. This was introduced with the purpose of improving accuracies in classification and this is determined through setting parameters to optimize penalties of the constant C and the bandwidth of the radial basis function (RBF) kernel, which are important steps to be taken in establishing an efficient and high-performance SVM model. Aiming at optimizing the parameters of SVM, it can be visualized through an Ant Colony Optimization (ACO) algorithm designed on a grid basis to select the parameters of C and Â automatically for SVM instead of randomly selecting parameters through individual experience and orthodox grid searching algorithm. Thus, through applying the above technique, the number of classification features can be reduced to simultaneously improve classification performance.

Gonzalez *et al*., [21] proposed a method for classifying single-trial ERPs using a combination of the Lifting Wavelet Transform (LWT), PSO (Particle Swarm Optimization and SVM techniques. Particularly noticeable are the LWT filters where the set of EEG channels and SVM parameters provide maximum classification accuracy during PSO searches. The authors evaluated the method's performance through offline analysis of BCI Competition 2 and 3 datasets. The proposed method achieved a similar or higher classification accuracy than that achieved by other methods. It adapted wavelet basis functions and channel sets that match the time-frequency and spatial properties of the P300 ERP.

Wang *et al*., [22] used GA-SVM hybrid algorithm with two purposes as selecting of the optimal feature subset and deciding the parameters for SVM classifier after the features extracted through the algorithm called Sample Entropy. The hybrid GA-SVM algorithm has a higher accuracy range and fewer inputted features when it is compared to standard GA-based feature selection and GA-based parameters optimization for SVM.

MATERIALS AND METHODS

Selecting Datasets: Dataset, evaluate methods which are proposed to be used in Data Set I in BCI Competition III. Method, using motor imagery from recorded ECoG readings. In a BCI experiment, a subject performs an imaginary movements of his/er tongue or left small finger. Based on these experiments researchers are able to timely acquire electrical brain activities Researchers make sure that every recordings acquired has sample rate of 1000Hz. Potential Recordings are stored as microvolt values after it amplifies. Thus, every included trial has an imagined tongue/ finger movement which is being recorded for the time period of 3 seconds. To avoid data reflecting visually evoked potentials, recording intervals must start with 0.5 seconds after the end of visual round. Brain activity for 278 trials was considered as training data and similar activity for100 trials was considered test data [23].

Support Vector Machine (SVM): This is a significant modern classification technique developed by Vapnik which has shown to perform strongly in a number of real-world problems, including BCI. The central idea is to separate data $X \subset \mathbb{R}^d$ from two classes by finding a weight vector $w \in \mathbb{R}^d$ and an offset $b \in \mathbb{R}$ of a hyper-plane

$$\begin{aligned} \mathrm{H}: \quad & \mathbb{R}^d \rightarrow \{-1,1\} \\ & x \mapsto sign(w.x+b) \end{aligned}$$

It is taken that the distance between the two classes is large and it is capable of intuitively providing theoretical guarantees in its generalization abilities. One variant of the algorithm consists of solving the following optimization problem:

$$\min_{w \in \mathbb{R}^d} \quad \|w\|_2 + C\sum_{i=1}^{n} \xi_i^2$$

$$s.t. \quad y_i\left(w.x^{(i)}+b\right) \geq 1-\xi_i \quad (i=1,...,n)$$

The parameters ξ_i are called slack variables and ensure that the problem has a solution in case the data is not linear separable. The margin is de- fined as $\gamma(X, Y, C)$

= $1/\|w\|_2$. In practice one has to trade-off between a low training error, e.g. $\Sigma\xi_i^2$ and its huge margin denoted by γ. The above trade-off is regularized through its parameter C. Thus, it is important to find a good value for C is part of the model selection procedure. If no prior knowledge is available C has to be estimated from the training data, e.g. by using cross validation. The value 2/C is also referred to as the ridge [24].

A kernel function is defined as. The Radial Basis function is given as $K(x_i, x_j) = \exp(-\gamma\|x_i - x_j\|^2)$, $\gamma > 0$:

$$K\left(x_i, x_j\right) = \exp\left(-\gamma\left\|x_i - x_j\right\|^2\right), \gamma > 0$$

A proper parameter setting improves accuracy in SVM classification is determined in SVM models through the modification of the RBF kernel with : C and gamma (c). Intuitively, the gamma parameter proposes the distance a single training example can reach, with low key meanings like 'far' and high key meanings like 'close' [23].

Apart from parameters in the kernel and SVM , the crucial role of data when being separated into two groups, due to the usage of data values to plot training examples in a high dimensional space under an SVM model. It is the responsibility of the kernel which ensure translating data to a high-dimensional space, but separation abilities mostly depends on the availability of possible set of features. A well-established fact is that the correlation of class features depends largely on the amount of influence a data requires when it is being separated into two groups. However, not every feature is positive and there are features which contribute negatively to the entire classification procedure. So the process to choose best sub-sets is crucial to improving SVM abilities to generalise models. So SVM optimization schemes focused on feature selection process [25].

CLONALG: The immune system which is characterized through its comprehensive biological processes is a crucial step to combating bodily diseases. It is known to have authority in terms of control, parallel to operative abilities and functional adaptation skills , out od which all the described features are seen as desirable qualities to solve intricate or messy problems incurred while using artificially intelligent machines. Thus, the above research illustrates how implementation of CLONALG (Clonal Selection Algorithm) is inspired by the acquired immunity theory in clonal selection mechanisms.

The given steps provide the underlying abilities of the CLONALG algorithm.

The Initialization Step: Initialisation involves a process of preparing fixed N sizes antibody pools out of which N is separated into two parts, M as a memory antibody section who represents the algorithm solutions eventually and R as the remaining antibody pool whose purpose is to introduce additional diversity.

The Loop: Next step involves the execution of numerous iterations among antigens exposed in the system. Singular rounds of exposed iterations are known as a generation and the amount of generations G a system can execute is configurable by a user, by utilizing problem stopping specific conditions in the system.

A Selected Antigen: Singular antigens are randomly chosen without being replaced from a current generation pool of antigens.

Exposure Level: When selected antigen levels are exposed through Affinity values which are calculated for antibodies against any antigen. It is the measure of similarity commonly used in Hamming distances and is dependent on the problem.

Selection Procedure: It is a set of n antibodies which are selected from a whole antibody pool which has the highest affinity with the antigen.

Cloning Process: When the selected set of antibodies are cloned in proportion to their rank based affinity.

Affinity Maturation (Mutation): The duplicate set of clones which are subjected to affinity maturation procedures to highten matching the given antigen in question. Here, the degree of maturation is inversely 6 proportional to their parent's affinity (rank based), meaning that the greater the affinity, the lower the mutation.

Clone Exposure: The clone is then exposed to the antigen and affinity measures are calculated.

Candidature Process: Antibodies with the highest level of affinity among clones which are then selected as a probable candidate for memory antibodies M placements. If an affinity of a candidate memory cell is higher than that of the highest stimulated antigen from the memory pool m, then it can replace the chosen antigen. Group replacements occur in a similar, but batched manner.

Replacement: Finally, the d individuals in the remaining r antigen pool with the lowest affinity are replaced with new random antibodies.

Finishing Process: Finally, the entire process is completed after the complete training procedure. The M memory component within an antigen pool is taken to be the solution for the above algorithms. It mostly depends on problem domains and solutions might be the single best individual antigen or the collective of all antigens in the pool.

Therefore, the CLONALG's pseudo optimization code is as follows [26]:

```
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 generates 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
```

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

The advantage of having CLONALG steps in the algorithm that evaluate the degree of similarity among cells is that it is possible to maintain a dynamic control of the number of network cells, allowing the determination of more parsimonious solutions.

RESULTS AND DISCUSSION

Table 1 value for Classification Accuracy, Recall, Precision and RMSE respectively. Figure 1 to 3 shows the result graph for the same. Figure 4 shows the best fitness.

Table 1: Classification Accuracy, Recall, Precision and RMSE

	Classification Accuracy	Recall	Precision	RMSE
SVM with RBF kernel and CLONALG optimization	91.37	0.91365	0.9158	0.1621
Clonalg Feature selection and SVM with RBF kernel and CLONALG optimization	94.96	0.9496	0.94975	0.1421
Fuzzy Classifier	93.88	0.93885	0.9394	0.1722
Clonalg Feature selection and Fuzzy Classifier	93.53	0.93525	0.93535	0.1673

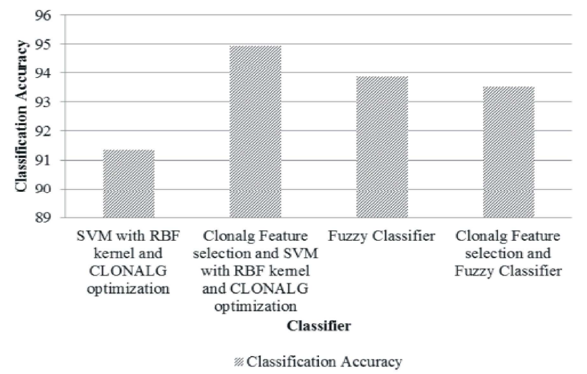

Fig. 1: Classification Accuracy

From Figure 1 shows the classification accuracy, it is observed that the proposed approach improved better performance than SVM with RBF kernel and CLONALG optimization and CLONALG Feature selection and SVM with RBF kernel and CLONALG optimization by 3.85%.

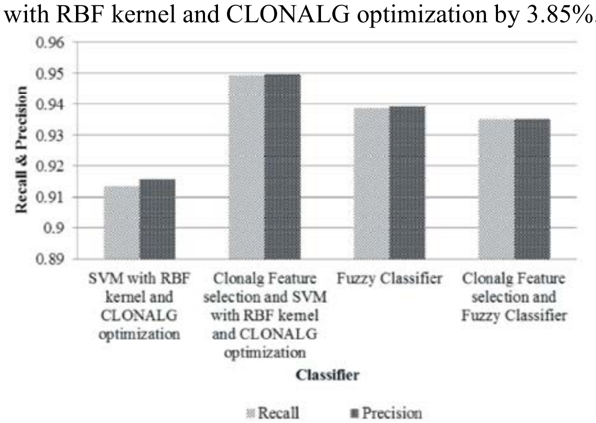

Fig. 2: Recall & Precision

From Figure 2 shows the recall and precision, it is observed that the proposed approach improved better performance than SVM with RBF kernel and CLONALG optimization by 0.24% and CLONALG Feature selection and SVM with RBF kernel and CLONALG optimization by 0.02%.

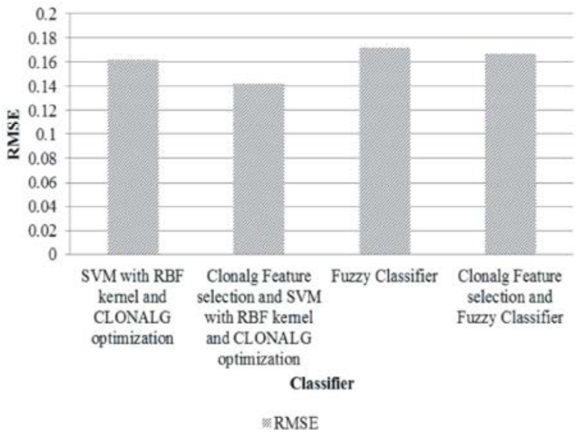

Fig. 3: RMSE

From Figure 3 shows the RMSE, it is observed that the proposed approach achieves better performance than Fuzzy Classifier and CLONALG Feature selection and Fuzzy Classifier by 19.15%.

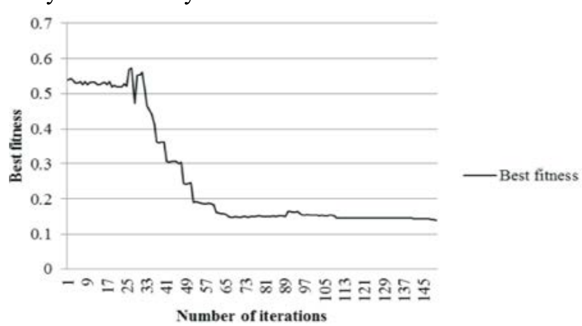

Fig 4: Best fitness

From figure 4 it is observed that the convergence occurred at iteration number 150.

CONCLUSION

ECoG includes a spatial scale between EEG and intracortical 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 artifacts and inconsistency and variability of user attention/intentions. CLONALG optimizes SVM. For intensification, the strategy works with many clones to improve it. Experiments were undertaken through tenfold cross validation and accuracy achieved is satisfactory but further work is needed for classification accuracy improvement. From result it is seen that the proposed method outperforms on accuracy, recall, precision than SVM with RBF kernel and CLONALG optimization and CLONALG Feature selection and SVM with RBF kernel and CLONALG optimization by 3.85%, by 0.24% and by 0.02% respectively. Also RMSE of the proposed approach achieves better performance than Fuzzy Classifier and CLONALG Feature selection and Fuzzy Classifier by 19.15%.

REFERENCES

1. Burns, A., H. Adeli and J.A. Buford, 2014. Brain-computer interface after nervous system injury. The Neuroscientist, 1073858414549015.
2. Yuan, H. and B. He, 2014. Brain–computer interfaces using sensorimotor rhythms: current state and future perspectives. Biomedical Engineering, IEEE Transactions on, 61(5): 1425-1435.
3. Young, B.M., Z. Nigogosyan, A. Remsik, L.M. Walton, J. Song, V.A. Nair and J.A. Sattin, 2015. Changes in functional connectivity correlate with behavioral gains in stroke patients after therapy using a brain-computer interface device. Interaction of BCI with the underlying neurological conditions in patients: pros and cons.
4. Hiremath, S.V., W. Chen, W. Wang, S. Foldes, T. Yang, E.C. Tyler-Kabara and M.L. Boninger, 2015. Brain computer interface learning for systems based on electrocorticography and intracortical microelectrode arrays. Frontiers in Integrative Neuroscience, pp: 9.
5. Naseer, N. and K.S. Hong, 2015. fNIRS-based brain-computer interfaces: a review. Frontiers in Human Neuroscience, pp: 9.
6. Zhang, X., D. Qiu and F. Chen, 2015. Support vector machine with parameter optimization by a novel hybrid method and its application to fault diagnosis. Neurocomputing, 149: 641-651.
7. Peng, Y. and B.L. Lu, 2015. Hybrid learning clonal selection algorithm.Information Sci., 296: 128-146
8. Yu, J., C. Li, W. Hong, S. Li and D. Mei, 2015. A new approach of rules extraction for word sense disambiguation by features of attributes. Applied Soft Computing, 27: 411-419.
9. Meyer, D. and F.T. Wien, 2015. Support vector machines. The Interface to libsvm in package e1071.

10. Rathipriya, N., S. Deepajothi and T. Rajendran, 2013. December). Classification of motor imagery ecog signals using support vector machine for brain computer interface. In Advanced Computing (IcoAC), 2013 Fifth International Conference on, pp: 63-66. IEEE.
11. Zhao, H.B., C.Y. Yu, C. Liu and H. Wang, 2010. October). ECoG-based brain-computer interface using relative wavelet energy and probabilistic neural network. In Biomedical Engineering and Informatics (BMEI), 2010 3rd International Conference on, 2: 873-877. IEEE.
12. Yan, S., H. Wang, C. Liu and H. Zhao, 2015. Electrocorticogram classification based on wavelet variance and Fisher linear discriminant analysis. In Control and Decision Conference (CCDC), 2015 27th Chinese, pp: 5404-5408. IEEE.
13. Song, C., R. Xu and B. Hong, 2014. Decoding of Chinese phoneme clusters using ECoG. In Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE, pp: 1278-1281.
14. Aydemir, Ö. and T. Kayıkçıoğlu, 2010. Motor imagery ECoG signals classification using wavelet transform features. In Signal Processing and Communications Applications Conference (SIU), 2010 IEEE 18th, pp 296-299.
15. Krusienski, D.J. and J.J. Shih, 2010. A case study on the relation between electroencephalographic and electrocorticographic event-related potentials. In Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE, pp: 6019-6022.
16. Bai, V.T., 2015. Feature Selection in Brain Computer Interface Using Genetics Method. In Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing (CIT/IUCC/DASC/PICOM), 2015 IEEE International Conference on, pp: 270-275.
17. Li, L., D. Xiong and X. Wu, 2011. Classification of imaginary movements in ECoG. In Bioinformatics and Biomedical Engineering, (iCBBE) 2011 5th International Conference on, pp: 1-3. IEEE.
18. Wei, Q. and W. Tu, 2008. Channel selection by genetic algorithms for classifying single-trial ECoG during motor imagery. In Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE, pp: 624-627.
19. Bai, Y., Z. Zhang and D. Ming, 2014. Feature selection and channel optimization for biometric identification based on visual evoked potentials. InDigital Signal Processing (DSP), 2014 19th International Conference on, pp: 772-776. IEEE.
20. Ding, S., 2009. Feature selection based F-score and ACO algorithm in support vector machine. In Knowledge Acquisition and Modeling, 2009. KAM'09. Second International Symposium on, 1: 19-23. IEEE.
21. Gonzalez, A., I. Nambu, H. Hokari, M. Iwahashi and T. Wada, 2013. Towards the Classification of Single-Trial Event-Related Potentials Using Adapted Wavelets and Particle Swarm Optimization. In Systems, Man and Cybernetics (SMC), 2013 IEEE International Conference on, pp: 3089-3094. IEEE.
22. Wang, L., G. Xu, J. Wang, S. Yang, L. Guo and W. Yan, 2011. GA-SVM based feature selection and parameters optimization for BCI research. In Natural Computation (ICNC), 2011 Seventh International Conference on, 1: 580-583. IEEE.
23. Gull, M.A., J. Iqbal and M.I. Tiwana, 2015. Spatial Temporal based Classification for Antebrachium and Carpus Movement of EEG Data Using Emotive Head set. Journal of Biomedical Engineering and Medical Imaging, 1(6).
24. Upadhyay, R., A. Manglick, D.K. Reddy, P.K. Padhy and P.K. Kankar, 2015. Channel optimization and nonlinear feature extraction for Electroencephalogram signals classification. Computers & Electrical Engineering, 45: 222-234.
25. Ma, Z., Z.H. Tan and J. Guo, 2016. Feature selection for neutral vector in EEG signal classification. Neurocomputing, 174: 937-945.
26. Datta, R. and K. Deb, 2015. Evolutionary Constrained Optimization: A Hybrid Approach. In Evolutionary Constrained Optimization, pp: 249-313. Springer India.