

Beta Artificial Bee Colony Algorithm for EMG Feature Selection



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1 Introduction

EMG signal is a bioelectrical signal expressed by the activity of muscle during contraction. EMG is a non-invasive technique, and it is related to the upper limb information of the body [1]. EMG data is collected by surface EMG (sEMG) sensors placed on the surface of the skin. sEMG sensors are mainly used in different types of experiments such as lab experiments, field experiments, etc. Muscular activity of the body can be recorded, measured, and analyzed to explore and identify various research areas such as biomechanics, rehabilitation, sports science, clinical diagnosis, man-machine interface, and so on. EMG signal can be applied into the development of an interface model for people with disabilities such as electric wheelchairs, prosthesis control, robotics (robot control), virtual world, and so on. In this work, prosthesis control based on non-invasive adaptive prosthetics is considered for classifying hand movements [2]. Recent scientific research has proposed various methods in the field of the hand prosthetics such as hybrid prosthetics, passive prosthetics, robotic hand prosthetics, and so on [3, 4]. The present work is based on the investigation of the robotic hand prosthetic followed by 67 intact subjects and 11 transradial amputated subjects. Generally, the upper link of hand prostheses is controlled using more than one EMG signal. There are many movements in the muscular activity of the amputees leading to various problems that need to be identified and isolated. To

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eliminate these problems, enhance classification performance by choosing the right feature selection techniques [2, 3, 5].

FS is a preprocessing and essential step to remove redundant and irrelevant information of the problem as well as reduce the number of feature and classifier complexity. There are three types of FS techniques: (i) filter techniques, (ii) wrapper techniques, and (iii) hybrid techniques. The filter technique is used for statistical techniques such as mutual information, distance information, and correlation information. Examples of filter techniques are correlation-based feature selection, information gain, ANOVA, principal component analysis (PCA), and so on [6]. Whereas the wrapper technique is based on finding the optimal feature subset from the actual feature set. It includes feature selection-based meta-heuristic algorithms such as binary artificial bee colony algorithm (BABC), binary particle swarm optimization (BPSO), binary ant colony optimization (BACO), binary crow search algorithm (BCSA) [7–10]. The third type of hybrid feature selection technique is a combination of filter and wrapper technique that improves the classification accuracy. Examples of hybrid techniques are hybrid serial GWO-WOA [11], TOPSIS-Jaya [12], and so on. Compared to all three techniques, the hybrid technique is faster than the wrapper technique, and the filter technique is a simple structure with a fast processing process. However, all feature selection techniques provide better classification accuracy with different domains and regions, therefore the major interest of researchers in the feature selection area.

In recent years, real-world problems are getting more and more challenging, thus requiring more flexible, robust, and efficient algorithms in feature selection. One of the most promising swarm algorithms of feature selection for optimization is artificial bee colony (ABC) and has great potential with proper modifications. It is a new approach proposed by Karaboga [13], and since then, there has been a rapid increase in the interest of ABC. ABC has been successfully applied to many fields like machine batch processing of a machine [14], designing two-channel quadrature mirror filter banks [15], loudspeaker design problems [16], etc. In [17], a two-archive multi-objective ABC algorithm (TMABC-FS) is developed for the cost-sensitive FS problem of machine learning [16, 17]. ABC has the potential of solving local and global optimization problems. Several benchmark functions [18] have been tested to validate the performance of ABC. As per no free lunch theorem, no specific meta-heuristic algorithm is regarded as best that gives best solution for all optimization problems. The standard ABC algorithm however demands alteration for many practical applications due to its inefficiency in balancing both exploration and exploitation phases during searching. The solution generated after each run by the solution search equation of the algorithm has an equal probability of being a positive or negative result. For ensuring better and effective results from the algorithm, the two phases need to be well balanced as excessive exploitations lead to premature convergence to local minima and excessive explorations result in slow convergence. Thus, Gaussian artificial bee colony (GABC) [19] was proposed to counterbalance between exploration and exploitation. It outperforms standard ABC by taking random values from Gaussian distribution over a uniform distribution.

Although GABC is better than the standard ABC, it still needs improvements in terms of convergence and better exploration capability. We propose a beta artificial bee colony (BetaABC) algorithm to further increase its performance by introducing beta distribution in search space. This algorithm avoids premature or slow convergence, and after comparison with ABC and GABC with different parameters, it proves to be better, in terms of global optimization. Hence, the key contributions of the proposed method are listed below:

1. A novel variant of ABC, i.e., beta artificial bee colony (BetaABC) is proposed and validated on 10 benchmark functions.
2. Binary beta artificial bee colony (BBABC)-based FS is proposed for EMG signal classification.
3. DWT is employed to extract various features from EMG signal.
4. The proposed BBABC is applied for FS and classification of prosthetic hand movements using EMG signal.
5. The extensive experiment is performed to validate proposed BBABC with BABC, and BGABC.

2 Methods and Implementation

2.1 EMG Data

The raw EMG data is taken from the public domain non-invasive adaptive prosthetics (NinaPro) dataset for prosthetic hands [3]. In this study, the third version of the NinaPro dataset (DB3) that comprises EMG signals acquired from 11 amputee people for 17 hand movements (Exercise A) is used. There are 12 EMG electrodes with a 2000 Hz sampling frequency which are used in the experiment. Each subject was asked to perform 6 movement repetitions with 5 s of action and 3 s of rest.

2.2 Feature Extraction Using DWT Method

Discrete wavelet transform (DWT) is a widely used feature extraction method in signal processing that decomposes signals in a time–frequency domain. The signals are decomposed into multi-resolution coefficients, i.e., low-pass filter and high-pass filter. Low-pass filters are represented in approximation levels (A) and high-pass filters are represented in detail levels (D) [20]. The popular mother wavelet-like sym4, sym6, coif4, coif5, db4, db6, bior2.2, bior2.4, and bior4.4 of the DWT method were selected to extract the features from raw EMG signals. Recent research shows that the decomposition at the fourth level with db6 gives promising results in EMG signal classification. Therefore, the DWT method at the fourth decomposition level with db6 is used in the current work [21, 22]. In literature, twenty-four popular statistical

Table 1 Twenty-four statistical EMG features

S. No	Feature	Feature name	S. No	Feature	Feature name
1	RMS	Root mean square	13	EWL	Enhanced wavelength
2	MAV	Mean absolute value	14	SI	Simple square integral
3	WL	Wavelength	15	MMAV	Modified mean absolute value
4	VAR	Variance of EMG	16	MMAV2	Modified mean absolute value 2
5	ZC	Zero crossing	17	DASDV	Difference absolute standard deviation value
6	AE	Average energy	18	VO	V-order
7	LD	Log detector	19	MYOP	Myopulse percentage rate
8	WA	Willison amplitude	20	IEMG	Integrated EMG
9	SKEW	Skewness	21	SD	Standard deviation
10	KURT	Kurtosis	22	DVARV	Difference variance value
11	MFL	Maximum fractal length	23	TM	Temporal moment
12	AAC	Average amplitude change	24	MAD	Mean absolute deviation

features have been used to extract valuable information from each wavelet coefficient as given in Table 1 [22–27].

2.3 Background

2.3.1 Artificial Bee Colony

ABC consists of two components: bees (the process of decision making for selection of the position of food) and food source (position in space). It defines two types of behavior: nectar source identification and food source abandonment. Also, the bees are categorized into three class namely—employed, onlooker, and scout bees [13]. The job of the employed bees is to visit identified food sources while the job of the scout bees are to search new food sources around the hive. The job of the onlooker bees is to stay and watch the employed bees at the hive in order to identify the food sources. In the whole process, some bees are employed to search the food randomly around the hive. These bees are responsible for collecting, bringing, and depositing some nectar from identified food sources to the hive. After depositing, their job is to share the information through various dance about quantity and quality of the nectar of food sources with the bees (onlookers) waiting in a hive [28]. The bee colony now enters a cycle of iterations and the following steps are followed: (1) after the information is shared, the employed bee either becomes onlooker after the food source is abandoned or continue to forage the site visited earlier; (2) onlookers in the hive will follow employed bees simultaneously based on the information received

to forage further on some memorized sources of food; and (3) some of the scouts will start random search spontaneously [13, 28, 29]. The food sources are randomly initialized using the below expression:

$$a_i = l_k + \text{rand}(0, 1) * (u_k - l_k) \quad (1)$$

where a_i is the i th solution in the population, k is a randomly selected parameter index, u_k and l_k are upper and lower bound constraints for the solution search space of objective function to be optimized. Onlooker bee selects the food sources influenced by employed bees based on the probability:

$$Pb_i = \text{fitness}_i / \sum_{n=1}^{SN} \text{fitness}_i \quad (2)$$

to calculate the fitness values, we use the following equation:

$$\text{fitness}_i = \begin{cases} \frac{1}{1+f} & \text{if } f \geq 0 \\ 1 + \text{abs}(f) & \text{if } f < 0 \end{cases} \quad (3)$$

The following equation is used for greedy selection to update the solution:

$$\left. \begin{array}{l} a = a_{\text{new}} \\ f = f_{\text{new}} \end{array} \right\} \text{if } \text{fitness}_{\text{new}} > \text{fitness}_i(a_i)$$

a and f remains the same if $\text{fitness}_{\text{new}} < \text{fitness}_i(a_i)$ (4)

where f represents the food source. Onlookers will explore all the locations that seem promising and might have a higher probability than other locations. The following equation is used to generate candidate food sources from the previously memorized ones as:

$$b_{i,j} = a_{i,j} + 2(r - 0.5)(a_{i,j} - a_{k,j}) \quad (5)$$

2.3.2 Gaussian Artificial Bee Colony (GABC)

A common problem with meta-heuristic methods is that poor balance between the exploitation and exploration capability and thus suffers from either very slow convergence due to excessive exploration or premature convergence due to excessive exploitation [19]. In GABC, the improvement has been made to generate candidate food sources as per the following alternative:

$$b_{i,j} = \begin{cases} a_{i,j} + \emptyset_{i,j}(a_{i,j} - a_{k,j}).\theta.\rho & \text{if } r_2 > z \\ a_{i,j} + \emptyset_{i,j}(a_{i,j} - a_{k,j}).2.\rho & \text{if } r_2 \leq z \end{cases} \quad (6)$$

where $\emptyset_{i,j} = 2.(r_1 - 0.5)$, \emptyset is a random number in the range $[-1,1]$, and i, j, k are indexes of dimension of a solution, and $r_1, r_2 \in [0,1]$ are random numbers generated from uniform distribution and

$$\rho = 0.5 - 0.25 \frac{\text{iter}}{\text{maxiter}} \quad (7)$$

and θ is a number generated from Gaussian distribution; iter and maxiter represent current and total iterations, respectively. The parameter z is used to balance the tradeoff between Gaussian and uniform distribution.

3 Proposed Methodology

3.1 Beta Artificial Bee Colony (BetaABC)

Although GABC is better than the standard ABC, it still needs improvements in terms of convergence. Therefore, we propose BetaABC to further avoid slow or premature convergence. The proposed method uses beta distribution over uniform or Gaussian distribution that increases the search space which in turn gives a better balance between exploration and exploitation capability. In GABC, a list of random samples is drawn from a normal distribution and Gaussian distribution. The distribution is dependent on many parameters like loc, scale, and size. The number of samples is equal to the value of the size of the argument. Furthermore, in each iteration, the results will be slightly different due to their randomness nature but will follow the same distribution and general shape. Unlike GABC, the proposed method uses beta distribution to draw samples. It has the probability distribution function

$$f(x; a, b) = \frac{1}{B(\alpha, \beta)} x^{\alpha-1} (1-x)^{\beta-1} \quad (8)$$

where B is the beta function

$$B(\alpha, \beta) = \int_0^1 t^{\alpha-1} (1-t)^{\beta-1} dt \quad (9)$$

where a and b are oats or an array of oats, size is int or tuple of int and α & β are positive values.

4 Proposed Binary BetaABC for EMG Feature Selection

The presence of redundant and irrelevant information in a problem makes the classification of EMG signals excessively difficult, which also reduces the performance of their classification models. Therefore, the proposed BetaABC is converted into its binary version called binary BetaABC (BBABC) to solve the feature selection problem in EMG signal classification. The dimension of the search space is equal to the number of features in EMG dataset. The following matrix G ($E \times F$) shows the possible solution to be selected as optimal feature subset. Here, E represents the population size, and F represents the number of features. Our main objective is to select S optimal features from the original EMG dataset, where $S \ll F$. The example of possible solution is given below:

$$G = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}$$

where G has a population size of 5 with 8 dimensions. Bit 1 shows the feature is selected, whereas bit 0 shows the feature is not selected. So the first solution represents the 1st, 3rd, 7th, and 8th features that were selected. The second solution represents the 1st, 3rd, 5th, and 7th features were selected, and so on.

Algorithm: Beta Artificial Bee Colony (BetaABC)

1. Initialize population of solutions $a_{i,j}$ using Eq. (1)
 2. Evaluate the population
 3. Run = 1
 4. Produce new food sources $b_{i,j}$ in the neighborhood of $a_{i,j}$ for employed bees using Eq. (6) with θ generated from Eqs. (8) and (9)
 5. Calculate probability values P_{bi} for $a_{i,j}$ with the help of their fitness values using the Eq. (2)
 6. Calculate the value of fitness _{i} using Eq. (3)
 7. Apply greedy selection process between $a_{i,j}$ and $b_{i,j}$ by using Eq. (4)
 8. Produce new food sources $b_{i,j}$ in the neighborhood of $a_{i,j}$ for onlooker using Eq. (6) with θ generated from Eqs. (8) and (9)
 9. Produce new positions bi for onlooker from the a_i selected depending on P_{bi} and evaluate by using Eq. (2)
 10. Calculate the value of fitness _{i} using Eq. (3)
 11. Apply greedy selection process for the onlookers between $a_{i,j}$ and $b_{i,j}$ by using Eq. (4)
 12. Find the abandoned sources, if exists, and replace them with new random solution a_i for scout using equation
 - $a_{i,j} = \min_j + \text{rand}(0, 1) * (\max_j - \min_j)$
 13. Memorize the position of best food source achieved so far
 14. Run = Run + 1
 15. Repeat step 4 to 14 until Run = Maximum runs
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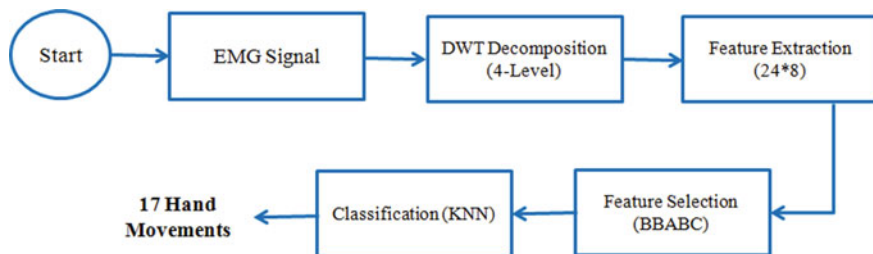


Fig. 1 Flow diagram of proposed BBABC for EMG signal classification

Figure 1 shows the flow diagram of the proposed BBABC for EMG feature selection and classification. Initially, raw EMG signals are preprocessed, and features are extracted from preprocessed EMG signal using DWT to form an original feature set. The extracted feature set contains 24 statistical features on 8 coefficients obtained at 4th level of DWT decomposition using db6 mother wavelet. The proposed BBABC is used to find the optimal feature subset from the extracted feature set. In the feature selection process, the fitness function is used to evaluate the performance of the classification. If the solutions give the same fitness value, then solution with fewer features is selected. Finally, the optimal feature subset obtained by the proposed BBABC is fed into the KNN classifier for EMG signal classification.

5 Experimental Analysis

Experimental analysis is divided into two sections: Section-I investigates the proposed BetaABC with ABC and GABC on 10 benchmark test functions that have been tested to validate its effectiveness and Section-II investigates the proposed BBABC for EMG feature selection on 11 amputee subjects.

Section-I: Experimental results of proposed BetaABC on benchmark functions

This section presents the comparative results of proposed BetaABC with ABC and GABC on different parameters. A set of 10 benchmark test functions have been used to validate the performance of BetaABC. These benchmark functions are used for the verification of many stochastic optimization algorithms. The necessary information about the functions, their mathematical representations, search range, and desired optimal solution is showcased in Table 2. All the test functions used for experimental verification are minimization functions.

The results of BetaABC are compared with the results of ABC and GABC for each benchmark function with different values of the parameter. The efficiency of the BetaABC algorithm depends on the parameter z that ranges from 0.1 to 0.9. The benchmark functions were run for several evaluations as the population size used for the experiment is 35, number of iteration is 100, and the value of z is

Table 2 Benchmark functions used in experiment

S. No	Function name	Mathematical representation	Search range	Optimal solution
1	Alpine	$f_1(x) : \sum_{i=1}^D x_i \sin(x_i) + 0.1x_i $	$[-10, 10]$	0
2	Booth	$f_2(x) : (x + 2y + 7)^2 + (2x + y - z)^2$	$[-10, 10]$	0
3	Beale	$f_3(x) : (1.5 - x + xy)^2 + (2.25 - x + xy^2)^2 + (2.625 - x + xy^3)^2$	$[-4.5, 4.5]$	0
4	Chung	$f_4(x) : (\sum_{i=1}^D x_i^2)^2$	$[-100, 100]$	0
5	Branin	$f_5(x) : (x_2 - 5.1x_1^2/4\pi^2 + 5x_1/\pi - 6)^2 + 10(1 - 1/8\pi)\cos(x_1) + 10$	$[-15, 15]$	0
6	Sphere	$f_6(x) : \sum_{i=1}^D x_i^2$	$[-100, 100]$	0
7	Griewank	$f_7(x) : \sum_{i=1}^D \frac{x_i^2}{4000} - \Pi \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	$[-600, 600]$	0
8	Rastrigin	$f_8(x) : \sum_{i=1}^D [x_i^2 - 10 \cos 2\pi x_i + 10n]$	$[-5.12, 5.12]$	0
9	Schaffer	$f_9(x) : 0.5 + \frac{\sin^2(x_1^2 + x_2^2) - 0.5}{1 + 0.001(x_1^2 + x_2^2)^2}$	$[-100, 100]$	0
10	Schwefel	$f_{10}(x) = 418.9829n - \sum x_i \sin(\sqrt{ x_i })$	$[-500, 500]$	0

0.5. The experiment was run 20 times independently for dimensions $D = 2$, and three statistical values, i.e., best, worst, and the average values, are noted from these experiments which are given in Table 3. It shows that the proposed BetaABC achieves higher or competitive results than ABC and GABC in all three statistical parameters. Convergence graphs based on fitness values are also plotted for comparison between ABC, GABC, and BetaABC on all benchmark functions as shown in Fig. 2. BetaABC is outperforming than ABC and GABC with suitable parameters.

Section-II: Experimental results of proposed BBABC on EMG signal classification

This section presents the performance of the proposed BBABC with BABC and BGABC for EMG feature selection. The EMG signals from 11 amputee subjects were collected from exercise A of the NinaPro DB3. Thereafter, the mother wavelet db6 of the DWT method was applied to decompose the EMG signal into the fourth decomposition level. Twenty-four statistical features were extracted from each DWT coefficient (four details and four approximations). In total, 2304 features (12 EMG channels \times 8 DWT coefficients \times 24 statistical features) were extracted from each EMG segment of each subject. The feature selection based on proposed BBABC is applied to select the optimal feature subset. The KNN classifier is used in the

Table 3 Fitness values of proposed BetaABC with ABC and GABC on 10 benchmark functions

		ABC	GABC	BetaABC
Alpine	Best	1.76E-12	4.54E-06	1.16E-12
	Worst	257.4853375	265.145999	216.5156087
	Avg	43.03078019	58.84823994	36.77360991
Booth	Best	0.24078979	0.11078979	0.003078979
	Worst	3.385294	14.20313	3.185294
	Avg	0.018105	0.138345	0.0018105
Beale	Best	0.34078979	0.18078979	0.06078979
	Worst	0.103797	0.092382	31.55422
	Avg	0.005416	0.001215	2.08101E-06
Chung	Best	1.26E-12	3.5421E-06	1.26E-12
	Worst	8,044,898.158	7,362,745.454	54,221,365,634
	Avg	87,181.57425	123,664.834	85,181.57425
Bramin	Best	20.05231234	20.08231234	19.67231234
	Worst	264.688204	371.9663214	121.6889116
	Avg	97.24972072	176.9312544	26.80310608
Sphere	Best	295.6037754	486.0067942	135.6037754
	Worst	292,744.4611	281,216.3629	2913.386937
	Avg	40,083.58003	68,324.75694	904.6985949
Griewank	Best	0.089460346	0.056780414	0.029460346
	Worst	0.059923658	0.071359047	0.029923658
	Avg	2.935520787	3.978498861	2.635520787
Rastrigin	Best	0.24972072	0.9312544	0.103106079
	Worst	1540.874042	1657.699314	1530.874042
	Avg	394.7383831	529.3521708	392.7383831
Schaffer	Best	0.21972072	0.7312544	0.103106079
	Worst	292,744.4611	281,216.3629	2913.386937
	Avg	40,083.58003	68,324.75694	904.6985949
Schwefel	Best	10.32063	13.14079	8.13034
	Worst	839.924873	2109.400154	2018.472328
	Avg	264.688204	371.9663214	121.6889116
Ranking (WITL)	Best	01119	010110	91110
	Worst	11019	21018	71013
	Avg	010110	010110	101010

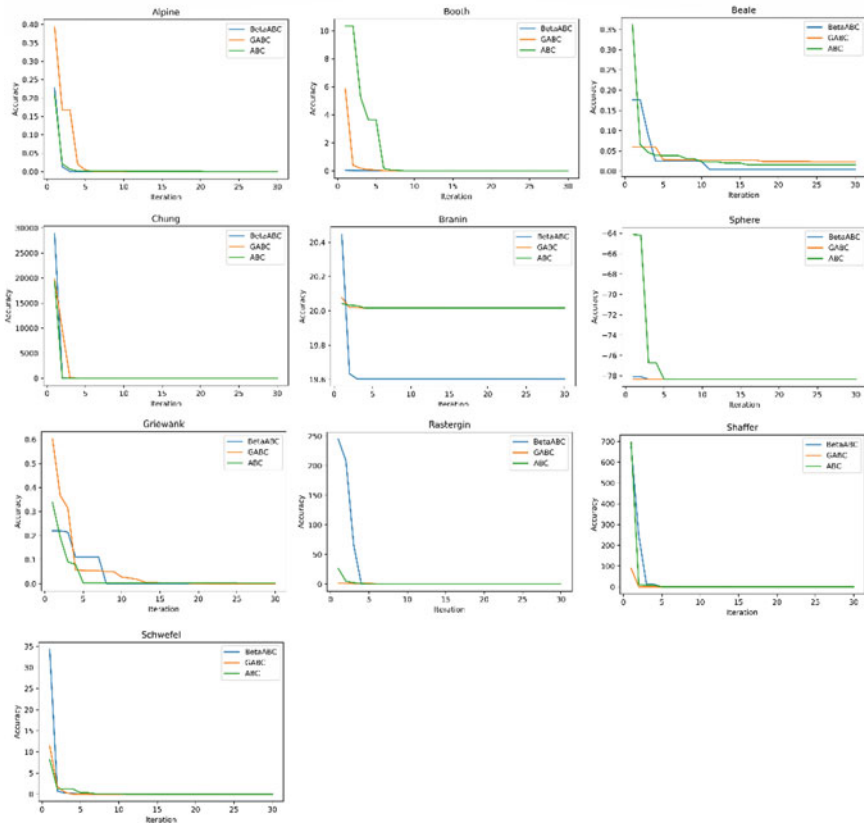


Fig. 2 Convergence graph of proposed BetaABC on 10 benchmark functions

experiment for the classification of 17 different hand movements from 11 amputee subjects. The two metrics, namely maximum accuracy and feature selection ratio, are used to evaluate the performance of the algorithms.

Table 4 shows the maximum accuracy and standard deviation of proposed BBABC with BABC and BGABC in which the best results are highlighted by bold text. It is observed that the proposed BBABC achieves the highest accuracy than the other two methods. The ranking of three methods is also given based on win/tie/loss (W/T/L) statistical measure. The W/T/L measure is also suggesting that the proposed BBABC-based feature selection method is outperforming than other methods. In Fig. 3, the comparison between BABC, BGABC, and BBABC is demonstrated by the convergence graph based on classification accuracy. The convergence graph is also showing that BBABC-based feature selection gives better classification accuracy than BABC and BGABC on 11 amputee people.

Table 5 shows the comparison of three feature selection methods BABC, BGABC, and BBABC based on feature selection ratio, i.e., the number of selected features

Table 4 Maximum classification accuracy with different ABC variants on 11 amputee subjects

Dataset		BABC	BGABC	BBABC
Subject 1	Avg	94.0983363	93.97058824	94.09902555
	Std	0.06302035	0.141347924	0.148025472
Subject 2	Avg	94.1176471	94.11764706	94.58057041
	Std	1.4283E-13	1.42832E-13	0.181260089
Subject 3	Avg	70.4426619	70.48128342	70.57070707
	Std	0.30304797	0.402824981	0.411057384
Subject 4	Avg	79.3850267	79.33155081	80.21717172
	Std	0.15265282	0.215227447	0.225440775
Subject 5	Avg	51.9266191	49.77421272	52.11194949
	Std	0.59257832	0.456221937	0.599318693
Subject 6	Avg	92.1078431	91.15418895	92.17498515
	Std	0.16090162	0.221699518	0.234779968
Subject 7	Avg	42.6619133	43.73291741	44.17142008
	Std	0.43284192	0.504772212	0.515929897
Subject 8	Avg	91.1764706	91.17647059	91.19647059
	Std	1.5711E-13	1.57115E-13	1.57115E-13
Subject 9	Avg	94.1161616	94.11764706	94.12764706
	Std	0.01477997	1.42832E-13	5.71327E-14
Subject 10	Avg	58.9913844	56.56565656	62.88264409
	Std	0.47960023	0.398101122	1.14265E-13
Subject 11	Avg	91.1586453	91.7409388	92.62147059
	Std	0.17735961	0.236479486	0.437655323
Ranking	WITL	0 0 11	0 0 11	1 1 0 0

divides by the total number of features. It is observed that the proposed BBABC method wins 7 times in selecting the minimum number of features.

6 Conclusion

This paper proposes a new variant of ABC algorithm called as BetaABC algorithm inspired from GABC algorithm aiming to improve its performance by maintaining a proper balance between the exploitation and exploration of the search space. The Uniform distribution used in the estimation of new search space solution is replaced with beta distribution which gives the better results than the existing algorithm. The performance of proposed BetaABC is evaluated on 10 benchmark functions and an obtained result suggests that it is outperforming the standard ABC and GABC. Further, a binary version of BetaABC called BBABC is proposed to solve the FS

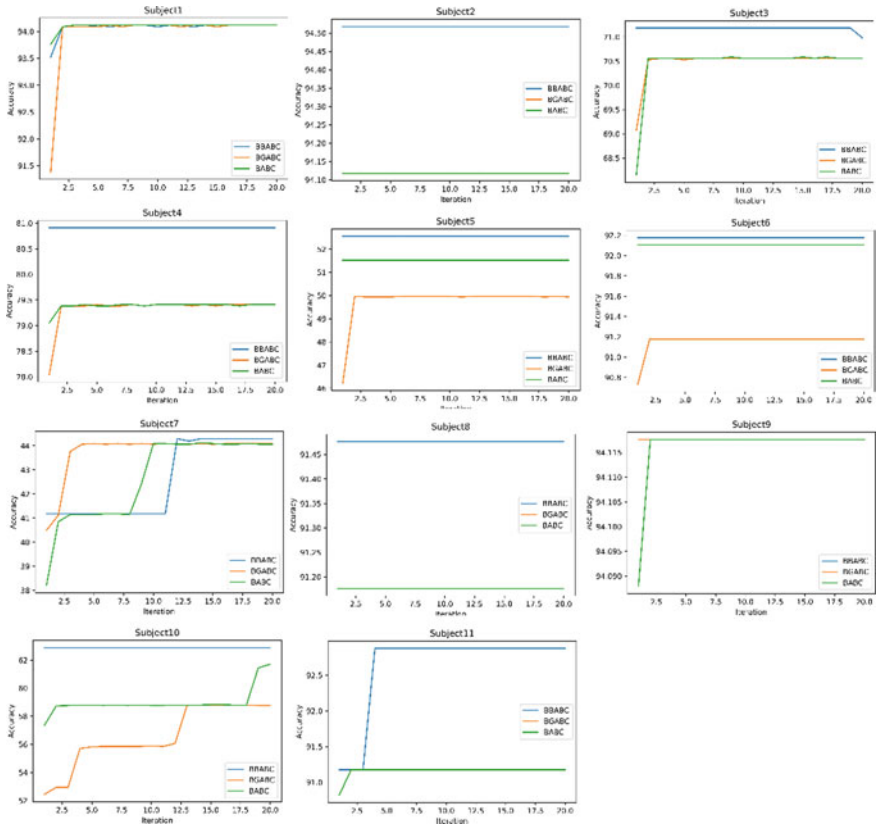


Fig. 3 Convergence graph of proposed BBABC with BABC and BGABC on 11 amputees

Table 5 Average feature selection ratio of BBABC with BABC and BGABC on 11 amputees

Dataset	BABC	BGABC	BBABC
Subject 1	0.51	0.45	0.33
Subject 2	0.47	0.42	0.31
Subject 3	0.5	0.47	0.37
Subject 4	0.5	0.5	0.49
Subject 5	0.49	0.54	0.3
Subject 6	0.4	0.41	0.54
Subject 7	0.41	0.41	0.27
Subject 8	0.48	0.44	0.51
Subject 9	0.71	0.53	0.75
Subject 10	0.5	0.49	0.27
Subject 11	0.48	0.63	0.6
Ranking	21019	21019	71014

problem of EMG signal classification. The accuracy and feature selection ratio is taken into consideration to validate the performance of the proposed BBABC with BABC and BGABC on 11 amputee subjects. It can be inferred from the experimental results and statistics that BBABC with appropriate parameters is giving either better results or competitive to other variants of ABC. Further improvements are to be expected keeping in view to the increasing popularity of the other variants of ABC.

References

1. Azhiri RB et al (2021) EMG signal classification using reflection coefficients and extreme value machine. arXiv preprint [arXiv:2106.10561](https://arxiv.org/abs/2106.10561)
2. Phinyomark A et al (2009) A novel feature extraction for robust EMG pattern recognition. arXiv preprint [arXiv:0912.3973](https://arxiv.org/abs/0912.3973)
3. Atzori M et al (2014) Electromyography data for non-invasive naturally-controlled robotic hand prostheses. *Sci Data* 1:1–13
4. Shi W-T et al (2018) A bionic hand controlled by hand gesture recognition based on surface EMG signals: A preliminary study. *Biocybernetics Biomed Eng* 38:126–135
5. Sharma T et al (2021) Decomposition and evaluation of SEMG for hand prostheses control. *Measurement* 186:110102
6. Bommert A et al (2020) Benchmark for filter methods for feature selection in high-dimensional classification data. *Comput Stat Data Anal* 143:106839
7. Chuang L-Y et al (2008) Improved binary PSO for feature selection using gene expression data. *Comput Biol Chem* 32:29–38
8. Karaboga D, Basturk B (2008) On the performance of artificial bee colony (ABC) algorithm. *Appl Soft Comput* 8:687–697
9. Aghdam MH et al (2009) Text feature selection using ant colony optimization. *Expert Syst Appl* 36:6843–6853
10. Chaudhuri A, Sahu TP (2021) Feature selection using Binary crow search algorithm with time varying flight length. *Expert Syst Appl* 168:114288
11. Mafarja M et al (2020) Efficient hybrid nature-inspired binary optimizers for feature selection. *Cogn Comput* 12:150–175
12. Chaudhuri A, Sahu TP (2021) A hybrid feature selection method based on Binary Jaya algorithm for micro-array data classification. *Comput Electr Eng* 90:106963
13. Karaboga D, Basturk B (2007) A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *J Global Optim* 39:459–471
14. Melouk S et al (2004) Minimizing makespan for single machine batch processing with non-identical job sizes using simulated annealing. *Int J Prod Econ* 87:141–147
15. Upendar J et al (2010) Design of two-channel quadrature mirror filter bank using particle swarm optimization. *Digital Signal Process* 20:304–313
16. Coelho LDS et al (2012) A chaotic approach of differential evolution optimization applied to loudspeaker design problem. *IEEE Trans Magn* 48:751–754
17. Zhang Y et al (2019) Cost-sensitive feature selection using two-archive multi-objective artificial bee colony algorithm. *Expert Syst Appl* 137:46–58
18. Tang K et al (2007) Benchmark functions for the CEC'2008 special session and competition on large scale global optimization. *Nat Inspired Comput Appl Lab USTC, China* 24:1–18
19. dos Santos Coelho L, Alotto P (2011) Gaussian artificial bee colony algorithm approach applied to Loney's solenoid benchmark problem. *IEEE Trans Magn* 47:1326–1329
20. Ahlawat V et al (2021) DWT-based hand movement identification of EMG signals using SVM. In: *Proceedings of international conference on communication and artificial intelligence, 2021*, pp 495–505

21. Chowdhury RH et al (2013) Surface electromyography signal processing and classification techniques. *Sensors* 13:12431–12466
22. Too J et al (2019) EMG feature selection and classification using a Pbest-guide binary particle swarm optimization. *Computation* 7:12
23. Too J et al (2019) Hybrid binary particle swarm optimization differential evolution-based feature selection for EMG signals classification. *Axioms* 8:79
24. Subasi A (2012) Classification of EMG signals using combined features and soft computing techniques. *Appl Soft Comput* 12:2188–2198
25. Too J et al (2019) Classification of hand movements based on discrete wavelet transform and enhanced feature extraction. *Int J Adv Comput Sci Appl* 10:83–89
26. Too J, Abdullah AR (2021) Opposition based competitive grey wolf optimizer for EMG feature selection. *Evol Intel* 14:1691–1705
27. Junior JJAM et al (2020) Feature selection and dimensionality reduction: an extensive comparison in hand gesture classification by sEMG in eight channels armband approach. *Biomed Signal Process Control* 59:101920
28. Karaboga D, Akay B (2009) A comparative study of artificial bee colony algorithm. *Appl Math Comput* 214:108–132
29. Cao Y et al (2019) An improved global best guided artificial bee colony algorithm for continuous optimization problems. *Clust Comput* 22:3011–3019