OPTIMIZING SVM FOR IMAGE RANKING USING ENHANCED ABC

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Abstract — It is saying that image is worthwhile 100 words. It is better way to explain anything using image. Here in this paper I am proposing an enhanced swarm based optimization algorithm to optimize image ranking procedure. I am using Support Vector Machine for image ranking procedure. Swarm based technique works on intelligent group work of member of particular swarm. There are many swarm based techniques are available now a days like ACO, PSO, ABC etc. ABC is working on intelligent behavior of honey bee swarm. To remove some of limitation of ABC algorithm here I hybridize ABC with Genetic algorithm. SVM is good classifier and by optimization process of weight vector we can get better performance of it. In this paper, we provide a thorough and extensive overview of most research work focusing on the application of ABC, with the expectation that it would serve as a reference material to both old and new, incoming researchers to the field, to support their understanding of current trends and assist their future research prospects and directions. Also new proposed architecture of Enhanced ABC algorithm, comparison between results of ABC and EABC for image ranking is also given here.

Keywords : Artificial Bee Colony Algorithm, Image Ranking, SVM, Swarm based techniques

I. INTRODUCTION

Optimization is the process to get optimum output with minimum or current input [1]. Image ranking is the process of classifying different images based on their content. In real word many times we search image by words it’s little bit cumbersome to find any image by word on internet because we can’t explain any image by phrase of few words. To get exact result we can search image by its content and it leads us to image based retrieval. For image based retrieval we need to rank image based on its content. In recent are many image ranking algorithm are available like SVM, ANN, Naive Bayes Classifier, k-Nearest Neighbor, Decision Trees etc. From all this algorithm SVM has high generalization capacity so it can correctly classify images with small set of training examples. Support Vector Machine is proposed by vapnic in 1995. SVM works based on statistical learning theory. Statistical learning theory is not only a tool for the theoretical analysis but also a tool for creating practical algorithms for pattern recognition.[7]. Many optimization techniques are available like Evolutionary algorithms, swarm based algorithms. I concentrate on swarm based techniques to optimize SVM. All swarm based techniques works based on main four principle which are: I) Positive feedback, II) negative feedback, III) fluctuations and IV) multiple interactions. Here I am working on artificial bee colony algorithm which works based on collective and clever behavior of honey bee swarm.

The remaining parts of the paper are organized as follows: Complete ABC algorithm is briefly outlined in Section II, image ranking algorithm is discussed in Section III. Section IV briefly explains proposed architecture of our EABC algorithm and finally in section V we will compare result of both ABC and EABC to optimize SVM.

II. THE ABC ALGORITHM

a) Forging behavior of bees in nature

In nature honey bees works on rule divide and concur. All the work of nest is divided between group of bees. All bees are divided in main three groups scout bee, onlooker bee and honey bee. Workings of all three groups are given below:

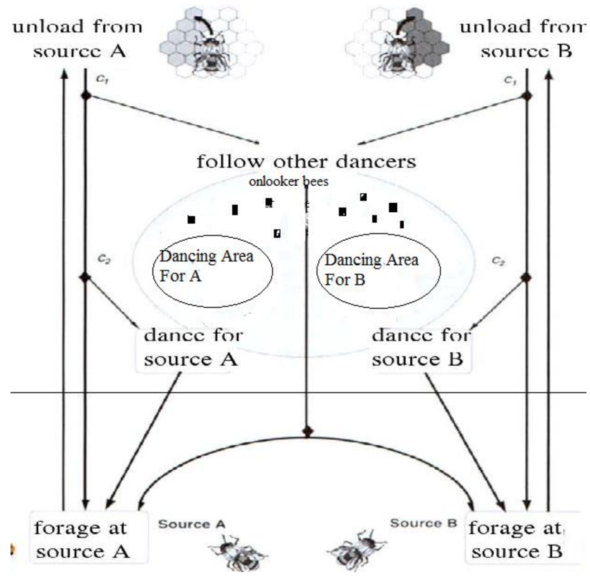

Figure 1: Intelligent behaviour of honey bee foraging

1) **Scout bee**: they start searching of food sources randomly without any information about the food source.
2) **Employ bee:** when scout bee finds any food source then it remembers information about that source and collects nectar from that source and also shares information about that source to other bees by performing waggle dance.
3) **Onlooker bee**: those bees watch the waggle dance performed by onlooker bee and then goes to the food source found by employ bee to collect the nectar.
4) **Waggle Dance**: this is the special type of movement performed by the employ bee to share the information about the food source with onlooker bees.

b) Mathematical model of ABC

The ABC consists of four main phases:

1. Initialization Phase:

The food sources, whose population size is SN, are randomly generated by scout bees. Each food source, represented by is an input vector to the optimization problem, has D variables and D is the dimension of searching space of the objective function to be optimized. The initial food sources are randomly produced via the expression (1)

$$x_m = l_i + \text{rand}(0,1) * (u_i - l_i)$$ ……….………………………………………………………………… ………...(1)

Where and are the upper and lower bound of the solution space of objective function, rand (0, 1) is a random number within the range [0, 1].

2. Employed Bee Phase:

Employed bee flies to a food source and finds a new food source within the neighborhood of the food source. The higher quantity food source is memorized by the employed bees. The food source information stored by employed bee will be shared with onlooker bees. A neighbor food source is determined and calculated by the following equation (2)

$$v_{mi} = x_{mi} + \varnothing_{mi}(x_{mi} - x_{ki})$$ …………..……………………………………………………… ……..….(2)

Where i is a randomly selected parameter index, is a randomly selected food source, is a random number within the range [-1, 1]. The range of this parameter can make an appropriate adjustment on specific issues. The fitness of food sources is essential in order to find the global optimal. The fitness is calculated by the following formula (3), after that a greedy selection is applied between x_m and f_m.

$$fit_m(x_m) = \begin{pmatrix} \frac{1}{1 + f_m(x_m)}, f_m(x_m) > 0 \\ 1 + |f_m(x_m)|, f_m(x_m) < 0 \end{pmatrix}$$ ……………………………………………………………… …...…….(3)

Where $f_m(x_m)$ is the objective function value of x_m.

3. Onlooker Bee Phase:

Onlooker bees calculates the profitability of food sources by observing the waggle dance in the dance area and then select a higher food source randomly. After that onlooker bees carry out randomly search in the neighborhood of food source. The quantity of a food source is evaluated by its profitability and the profitability of all food sources. Pm is determined by the formula

$$p_m = \frac{fit_m(x_m)}{\sum_{m=1}^{SN} fit_m(x_m)}$$ ……………………………………………………………………….……… ……….....(4)

Where $fit_m(x_m)$ is the fitness of x_m.

Onlooker bees search the neighborhood of food source according to the expression (5)

$$v_{mi} = x_{mi} + \varnothing_{mi}(x_{mi} - x_{ki})$$ ………………………………………………………………..……… ………...(5)

4. Scout Phase:

If the profitability of food source cannot be improved and the times of unchanged greater than the predetermined number of trials, which called "limit", the solutions will be abandoned by scout bees. Then, the new solutions are randomly searched by the scout bees. The new solution will be discovered by the scout by using the expression (6)

$x_m = l_i + rand(0,1)*(u_i - l_i)$ ....
...........(6)

$rand(0,1)$ is a random number within the range [0,1], and are the upper and lower bound of the solution space of objective function.[5]

c) Merits & Demerits of ABC

❖ Merits

1. ABC is flexible so can easily modified and hybridize with other algorithm.[3]
2. ABC is quite robust and not need to give any starting point.[3]
3. The ABC algorithm employs distributed computation, which avoids premature convergence.[4]

❖ Demerits

1. There is no centralized processor to guide the bees system towards good solutions[5]
2. This algorithm has slower convergence than other heuristic-based algorithms.[6]
3. There does not exist any standard software for the ABC algorithm as well.[1]

III. PROPOSED ARCHITECTURE OF OUR EABC ALGORITHM

By analysis of different optimization technique it is clear that ABC overcomes many limitations of current optimization techniques. And from one of the advantage of ABC is that we can also remove limitation of ABC by modifying it.

One of the drawback of ABC is that it stuck at local optima and we can't get global optimal solution. To overcome this drawback we hybridize ABC with genetic algorithm.

Here architecture of proposed system is given below:

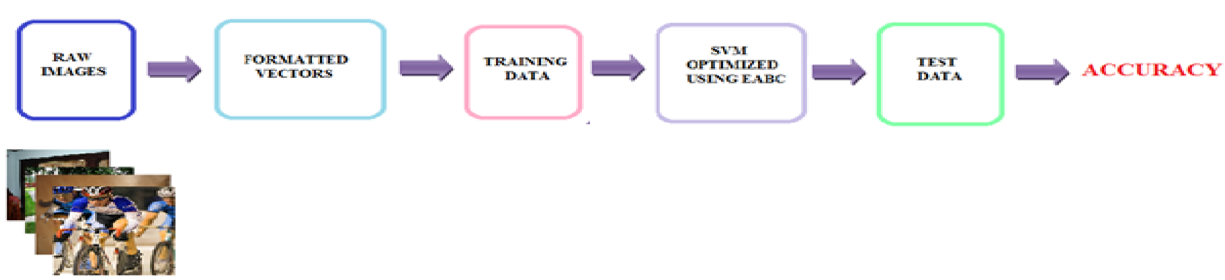

Figure 2 : Architecture of Proposed Miner

Stage 1: Input Raw Images

This is the very first stage where the input is fed to the system. For mining problem we have considered combination of images from real world. Main purpose of our proposed system is to rank all images that from which class particular image belongs.

Stage 2: Formatted Vectors

At this basic step histogram of image is build from image using key features and dimensions of image. For this process first we use SIFT features of image. Then this vector quantized into visual words. The frequency of each visual words is then recorded in a histogram. And final vector for image is a combination of these histograms.

Stage-3 Training images

Our EABC miner is supervised miner so we have to give some training images to train our miner. For training process we provide set of images from any particular class and also we can separate particular images in raw images by .mat file.

Stage 4- Enhanced ABC Algorithm to optimize SVM classifier

This is the heart of our system. Entire process of ranking starting from training to validation is done at this stage. Main work of our EABC optimization algorithm is to find out optimal feature vector.

Stage-5 Training images

A validation set is required to validate our ranking results. This image set is directly given from raw data which contains combinations of all class images. It is very much alike the training set but main difference is that it contains all class images and our miner provides resulted set of images which is from same class.

Stage 6- Output Ranked Image set & Accuracy check

This is the output of our miner. Here we display possible 64 images from our raw data which belongs to same class. Here we also calculate that how many images are correctly retrieved and based on that calculation accuracy is calculated of our system.

IV. COMPARISON OF RESULT BETWEEN ABC & EABC

To verify the effectiveness of the ABC algorithm, we conducted experiments on different types of class from various real domains. The aim behind using different class images for experimentation is to prove the consistency of the SVM-EABC classifier in different domains. Here I have given description of two datasets which I am using in this experiment.

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Table 1 : PASCAL Dataset description

PASCAL VOC 2007 benchmark	
Class	Number of Images
airplane	238
Person	2008
Motorbike	245
Car	713
Horse	287
Background	1455

Table 2 : Caltech-101 Dataset Description

Caltech-101 benchmark dataset	
Class	Number of Images
animal	356
Person	1692
Bird	856
Car	954
Background	1576

V. RESULT ANALYSIS

The parameters of the ABC algorithm were set to the same value for all the dataset problems: Colony size (NP = 20), number of food sources NP/2, limit = 100 and the maximum number of cycles was MCN = 1000.

Here result of our SVM-ABC classifier is compared with pure SVM classifier for different class images and for two benchmark image datasets. Comparison between pure SVM and SVM-ABC is given using chart representation for different class images.

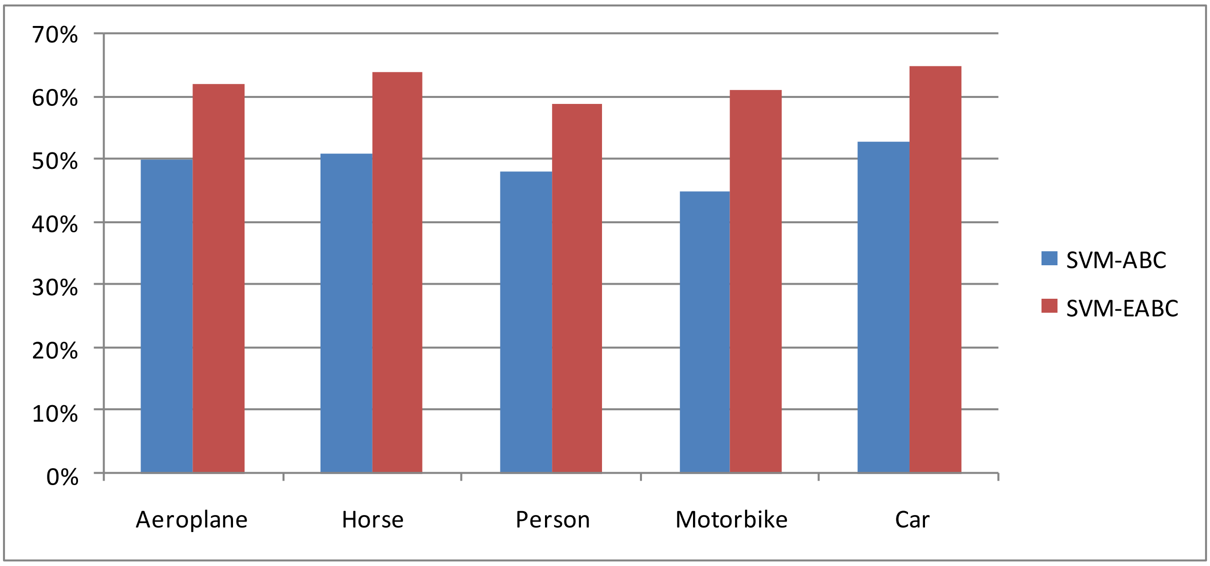

Figure 3 : comparison of performance of SVM-ABC and SVM-EABC on PASCAL dataset

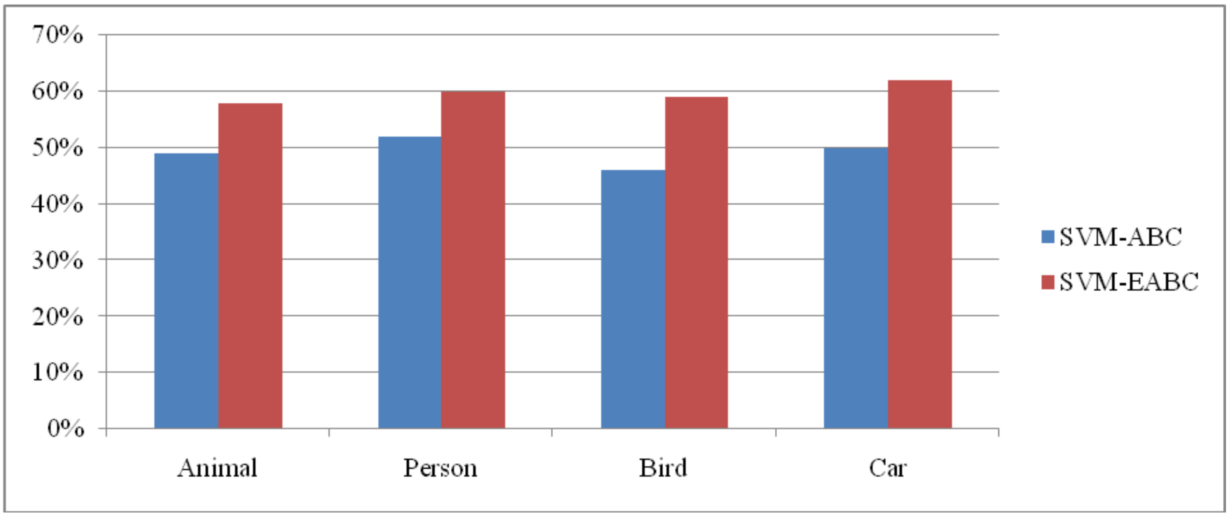

Figure 4 : comparison of performance of SVM-ABC and SVM-EABC on Caltech-101 dataset

From result graph it is clear that SVM-EABC gives better performance than SVM-ABC.

VI. CONCLUSION

In this paper, variety of research article in the domain of ABC has studied. From the in depth literature survey, it is observed that a large part of research was concentrated towards modifying the ABC algorithm to solve a variety of problems, including engineering design problems, scheduling problems, data miming problems etc. Although ABC has great potential, it was clear to the scientific community that some modifications to the original structure are still necessary in order to significantly improve its performance. Further, in this paper I have given a swarm based Enhanced ABC approach for optimizing SVM image ranking. By analysis of result of experiments it is clear that EABC is more promising than ABC. As a future work we can also implement EABC for remote sensing and different type of images.

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REFERENCES

[1]. Karaboga D., Basturk B., A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm, Journal of Global Optimization 39, 459- 471, 2007.

[2]. Fahad S. Abu-Mouti, Mohamed E. El-Hawary "Overview of Artificial Bee Colony (ABC) Algorithm and Its applications", IEEE 2012

[3]. R.S. Rao, SVL Narasimham, and M. Ramalingaraju. Optimization of distribution network configuration for loss reduction using artificial bee colony algorithm. International Journal of Electrical Power and Energy Systems Engineering, 1(2):116-122, 2008.

[4]. Beatriz A. Garro, Humberto Sossa, Roberto A. V´azquez, Artificial Neural Network Synthesis by means of Artificial Bee Colony (ABC) Algorithm, 978-1-4244-7835-4/11/$26.00 ©2011 IEEE

[5]. Karaboga, D. and Basturk, B., On the performance of artificial bee colony (ABC) algorithm, Applied Soft Computing, 8, 687-697, 2008.

[6]. Basturk, B. and Karaboga, D., An artificial bee colony (ABC) algorithm for numeric function optimization, Proceedings of the IEEE Swarm Intelligence Symposium, Indianapolis, USA, 2006.

[7]. Zhi-Gang Fan, Kai-An Wang, Feature Selection for Fast Image Classification with Support Vector Machines, Springer-Verlag Berlin Heidelberg 2004

[8]. Baykasoglu, L. Ozbakir, and P. Tapkan. Artificial bee colony algorithm and its application to generalized assignment problem. Swarm Intelligence: Focus on Ant and Particle Swarm Optimization, 2007, 113-144.

[9]. Haiyan Quan and Xinling Shi. On the analysis of performance of the improved artificial-bee-colony algorithm, in natural computation, 7, 2008, 654-658.

[10]. H. Narasimhan. Parallel artificial bee colony (pabc) algorithm. In Nature & Biologically Inspired Computing, 2009. World Congress on, 2009, 306-311.

[11]. P.W. Tsai, J.S. Pan, B.Y. Liao, and S.C. Chu. Enhanced artificial bee colony optimization. International Journal of Innovative Computing, Information and Control, 2009, 5(12).

[12]. B. Akay and D. Karaboga. A modified artificial bee colony algorithm for real parameter optimization. Information Sciences, 2010.

[13]. M. Sonmez. Artificial bee colony algorithm for optimization of truss structures. Applied Soft Computing, 11, 2010, 2406-2418.

[14]. R. Luo, T.S. Pan, P.W. Tsai, and J.S. Pan. Parallelized artificial bee colony with ripple-communication strategy. In Genetic and Evolutionary Computing (ICGEC), 2010 Fourth International Conference on, IEEE, 2010, 350–353.

[15]. Wenping Zou, Young Zhu, Hanning Chen, Xin Sui, A clustering approach using cooperative artificial bee colony algorithm, Hindawi publishing corporation, 21(459796), 2010, 21-37.

[16]. D. Karaboga and B. Akay. A modified artificial bee colony (ABC) algorithm for constrained optimization problems. Applied Soft Computing, 11, 2011, 3021-3031.

[17]. Tarun Kumar, Millie Pant, V.P. Singh, Artificial bee colony algorithm with self-adaptive colony size, proceeding of the 2nd international conference on swarm, evolutionary and memtic computing , 1, 2008, 593-600.

[18]. Bin Wu and Chu hua Qian. Differential artificial bee colony algorithm for global numerical optimization, in journal of computers, 6(5), 2011, 841-848.

[19]. M. El-Abd. Opposition-based artificial bee colony algorithm. In Proceedings of the 13th annual conference on Genetic and evolutionary computation, ACM, 2011,116.

