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4 authors:

Noor Elaiza Abdul Khalid
Universiti Teknologi MARA

Norharyati Md Ariff
Universiti Teknologi MARA

Saadiah Yahya
Universiti Teknologi MARA

Noorhayati Mohamed Noor
Universiti Teknologi MARA

A Review of Bio-inspired Algorithms as Image processing Techniques

Noor Elaiza Abdul Khalid[1],Norharyati Md Ariff[1], , Saadiah Yahya[1], Noorhayati Mohamed Noor[1]

[1] Faculty of Computer and Mathematical Sciences
Universiti Teknologi MARA
40450 Shah Alam, Selangor, Malaysia
Tel: +6012-5591341, E-mail: sakurayati@yahoo.com

Abstract. This paper reviews 80 out of 130 bio-inspired Algorithm (BIAs) researches published in google scholar and IEEExplore between the periods of 1995 to 2010 used to solve image processing problems. BIAs has been successfully applied in many sciences, medical and engineering fields. The evolving, dynamic and meta-heuristics nature of BIAs makes it more robust, accurate and efficient in solving image processing problems. However finding the appropriate BIAs that matches the problem at hand is a tedious and difficult task. The BIAs investigated in this study are Genetic Algorithms, Evolutionary strategies, Genetic programming, memetic algorithms, swarm intelligence and artificial immune system. The publications are categorized by year of publication, by specific BIAs and by application. The statistics shows exponential increases in the application of BIAs to solve image processing problems and some algorithms have yet to be explored.

Keyword: Evolutionary Algorithm, Artificial Intelligent, Image Processing, Bioinspired Algorithm.

1 Introduction

The human eye and brain are biological systems that have the capability to adapt to changes, act sensors and have very reliable processor that are able to enhance, segment, register and recognize features of visions or images. Computer vision attempts to emulate these capabilities. Image enhancement, feature extraction, segmentation and registration plays a big role in analysing images in field such as medical[6][9][22][25][40], geosciences[28], remote sensing[1], facial extraction[19], biometrics[30][39] and many more.[42][47]. The main challenges in these type of application is to find the most suitable, accurate, faster and robust algorithm. As To date most algorithm have been design for customary use only thus there is a need to find a more adaptable and dynamic way.

Biological systems have natural capability to adapt to changes by learning, it's evolving, resiliant and robust. Metaphoring these system into algorithms introduced bio-inspired algorithms (BIAs) which has become popular in solving problems in virtually any area. Three main branches of BIAs are evolutionary algorithms (EAs), swarm intelligence (SI) and bacterial foraging algorithms (BFAs) which loosely bind the topics of connectionism, social behaviour and emergence based on the understanding of biological systems, genetic evolution, animal behaviours and bacterial foraging patterns. BIAs has drawn considerable research interests in the area of science and engineering of which in this case focus on the image processing area. However determining the suitable algorithm is a difficult task. The objective of this survey is to provide a better understanding of the application of bio-inspired algorithm as intelligent image technique.This paper overviews and compares three branches of Bio-inspired Algorithms (BIAs) applied in the area of image processing. Only four image processing area will be explored; image segmentation; feature extraction; image enhancement and image registration. Discussion includes the steps in each algorithm and their performance in terms of convergence, complexity, accuracy, speed and the optimum solutions.

2 Methodology

The source website of scientific paper related to BIAs applied in image processing are Google Scholar and IEEExplore. The reasons why these sources were chosen are, it provides simple way to broadly search for scholarly literature and helps to find relevant works across the world of scholarly research. Even though 130 papers between the period of 1995 to 2010 related to BIAs in various applications are found, only 80 papers appliy the various BIAs in the area of image processing. *Bio-inspired Algorithms (BIAs)* can be divided into three main type that is the evolutionary algorithms, swarm intelligence (SI) and bacteria foraging algorithm (BFAs).

Evolutionary Algorithm (EA) attempts to solve complex problems by mimicking Darwinian evolution where individuals in a population continuously compete with each other in the process of searching for optimal solutions [3]. As the history of the field suggests, there are many different variants of Evolutionary Algorithms (EAs). The common underlying idea behind all these techniques is the same: given a population of individuals, the environmental pressure causes natural selection (survival of the fittest) and this causes a rise in the fitness of the population. Given a quality function to be maximized, we can randomly create a set of candidate solutions. Based on this understanding, a family of EAs, known as the genetic algorithm (GA) [4] [8], evolutionary strategy (ES)[9], genetic programming (GP)[10], Selfish gene (SFGA)[11,12] and Memetic algorithm (MA) [13] have been developed. Members of the

EA family share large number of common features and its population-based stochastic search algorithms perform best-to-survive criteria. Each algorithm commences by creating initial population of feasible solutions, and evolves iteratively from one generation to the next towards the best solution. Fitness-based selection takes place within the population. Diversity is introduced via mutations to uncover optimum solutions [8].

Selfish gene algorithm is a new member of EAs. It is focus on the fitness of the genes rather than the individuals. It does not have any crossover or mutation and its population store the genetic material which models the gene pool concept namely “Virtual Population”. This population presents the number of individuals, and their specific identity represented by genome. Explicitly distinguished location in the genome is locus and the value is allele. The success of alleles is based on the frequency it appears in the virtual population. Generally evolution means, that organism which succeeds will increase its allele’s frequency at the expense of its children and on the other hand organism which fails will decreases its allele’s frequency [11,101]. The selfish gene algorithm has been successfully tested in several problems such as Automatic Test Pattern Generation for digital circuits [101], multiple knapsack problem [11] and optimization method [107].

Swarm Intelligence (SI) is designed based on collective behavior of decentralized, self-organized systems that occurs naturally or artificially. Particle swarm optimization (PSO) is a population based stochastic optimization technique invented by Eberhart and Kennedy in 1995, motivated by social behavior of fish schooling [86]. The system started with initializing random solution population called particles and searches for optimal solution by updating generations. These particles fly through the problem space following the current optimum particles. PSO have proven to be successfully applied in scientific and various other purposes [93].

In recent years, Bacterial Foraging Algorithms (BFAs) have emerged as another new branch of BIAs, which inherit the characteristics of bacterial foraging patterns such as chemo taxis, metabolism, reproduction and quorum sensing. This remarkable information processing biological system translates AIS [94]. AIS can be applied as Negative Selection Mechanism [94], and the clonal selection algorithm [91].

2.1 Bio-inspired Algorithm Matrix

Table 1 tabulates specifically nine algorithmic features in the Bio-inspired algorithm Matrix aligning the various BIAS algorithms.

Table 1. Bio-inspired Algorithm Matrix

Features	GA	SFGA	MA	ES	GP	PSO	AIS
Encoding	Binary string, char, vector	real number	real number	real number	Symbolic alphabet	Binary string, char, vector	Attribute strings
Population	Yes	Yes Virtual Pop.	Yes	Yes	Yes	Yes-using particles	Component concentration/ network
Selection	Random, Tournament, Roulette Wheel	Random	Random or using heuristic	Yes same as GA	Yes same as GA	No selection	Random
Crossover	Yes	No	Yes	Yes	Yes	No	No
Mutation	Yes	Yes	Yes	Yes	Yes	No	Yes
Fitness Function	Yes	Yes	Yes	Yes	Yes	Yes	Recognition /Object
Generation	Yes	No	Yes	Yes	Yes	No	Iteration
Locus	No	Yes	No	No	No	No	No
Alleles	No	Yes	No	No	No	No	No
Local search	No	No	Yes	No	No	No	No
No of steps	7	4	4	8	6	5	Many

Encoding is the stage where chromosomes are represented as binary strings, char and vectors in GA and PSO; list of real number in SFGA and MA; symbolic tree in GP and attributes strings in AIS. BIAs parent selections stage can employ selection methods such as random, stochastic technique of roulette and tournament selection. Only MA uses heuristic search to select individuals from its population. Population size is very important for all BIAs algorithms variant, as limited population size produce low quality solutions [14]. The recombination or crossover stage is present in GA, MA, ES, GP and AIS. Among the types of crossover operation are single point, two point, uniform and arithmetic crossovers. Fitness function stage is important in all BIAs. It is a heuristic function that measures the performance of an individual chromosome. The fitness function establishes the basis f
or selecting chromosomes that will be mated during the reproduction in EAs and BFAs and best particles in PSO. The generation stage is used to repeat the process until it finds the most optimum values. Only SFGA and PSO do not include this stage.

Table 2 shows a comparison of five performance evaluation features of the bio-inspired algorithms that is the convergence rate, the algorithm complexity, the accuracy in finding solutions, the processing speed and the rate of achieving the optimal solutions.

Table 2. The performance evaluation matrix of the bio-inspired algorithms

Performance Features	GA [98,100]	SFGA [11,12,101]	MA [13,99,104]	ES [9,102]	GP [10,103]	PSO [95,98]	AIS [91,94,106]
Convergence	Difficult	Fast	Fast	difficult	difficult	Moderate	Difficult
complexity	Simple	Simple	simple	simple	difficult	Moderate	Difficult
Accuracy	Low	Reliable	reliable	moderate	low	Reliable	Low
Speed	Slow	Fast	Fast	slow	slow	Fast	Slow
Optimum sol.	Slow	Faster	faster	slow	slow	Fast	Slow

GA, ES, GP and AIS have difficulties in converging as the probability of making progress decreases rapidly as the minimum/maximum is approached. Thus, these algorithms are often hybridized with other techniques to improve their performance. [13] uses meta-heuristic population in GA and successfully resolved many optimization problems. However, premature convergence narrows down its ability to find many solutions. In the bid to reduce premature convergence possibility an algorithm that hybridized the classical GA with local search technique and named as Memetic [15], hybridized PSO and GA to counter the problems of early convergence in PSO and slow convergence in GA for global maximization.

The application of BIAs is becoming more and more popular in the area of image processing such as image segmentation, image enhancement, image restoration, image analysis, feature extraction, feature selection and face detection. Thus, this paper investigates the application of BIAs in the various area of image processing.

3 Results and discussion

The results of the investigation are discussed in two main sections; the general statistical BIAs application and the detail of image processing area where each BIAs are applied.

3.1 Population of BIAs Applications between 1995-2010

Researches that apply BIAs in image processing began around the 1990s. The 130 BIAs publications used in this review are 1995 to 2010. Figure 1 shows the application of BIAs Algorithm by year. An obvious observation is that there is an increasing amount of research using BIAs. BIAs has become popular choice of algorithm in various applications.

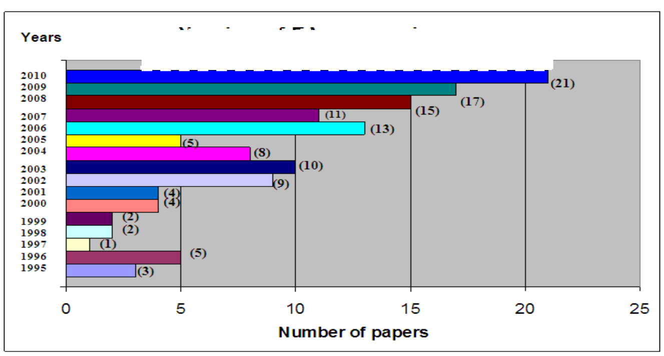

Fig.1. BIAs publications by year

3.2 Statistics of BIAs in Image Processing

Out of 130 papers on BIAs algorithm found only 80 papers are applied in image processing. Most of the researches are centered in the area of image extraction (47%) and image segmentation (31%). Only a small number of researches are done in image enhancement (13%) and registration (9%). This can be seen in Figure 2.

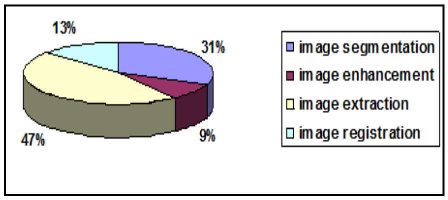

Fig. 2. A pie chart of statistical analysis of the Bio-inspired Algorithmn in Image processing techniques.

The area of image extraction and feature extraction is extremely popular technique that used BIAs. The applications include the use of image extraction for remote sensing [16-17], development of robust active contour techniques which are suitable for the extraction of the head boundary [18], facial feature extraction will automatically extract features from various video images effectively [19] and memetic algorithm for intelligent feature extraction that will generate representation for isolated handwritten symbols [20].

Image segmentation comes second in popularity where most publications are either new application or invention related to image segmentation. It covers fields such as medical segmentation [21][9], texture segmentation [22][61][63], multi-objective segmentation [7], image color segmentation [44] and graph-based segmentation [96].

Most of the BIAs methods use in image registration is evolution strategies. It is useful for image registration because an invariant reference needs to be established within each source image. ES is capable of discovering transformations of larger scope [23]. Similar to application by Yuan X et al [9], ES is used in image registration via feature matching. The BIAs are enhanced by adding other features that can lower computational cost, high accuracy regardless of the magnitude of transformation required and reduce noise condition. In addition, various BIAs are used in 3D-feature based image registration [24][47]. Image registration has been applied to a broad range of situations from remote sensing to medical images or artificial vision [16-17], CAD systems [97] and other different techniques [24].

Finally BIAs increase robustness and efficiency in image enhancement [25] in applications such as automatic fingerprint identification system [26] and amplifying image contrast while removing noise [27]. A more detail view of BIAs applied in each image processing area is depicted as a spider diagram in Figure 3. The spider diagram is used as a visual technique [2] to model the various BIAs applied to image processing area.

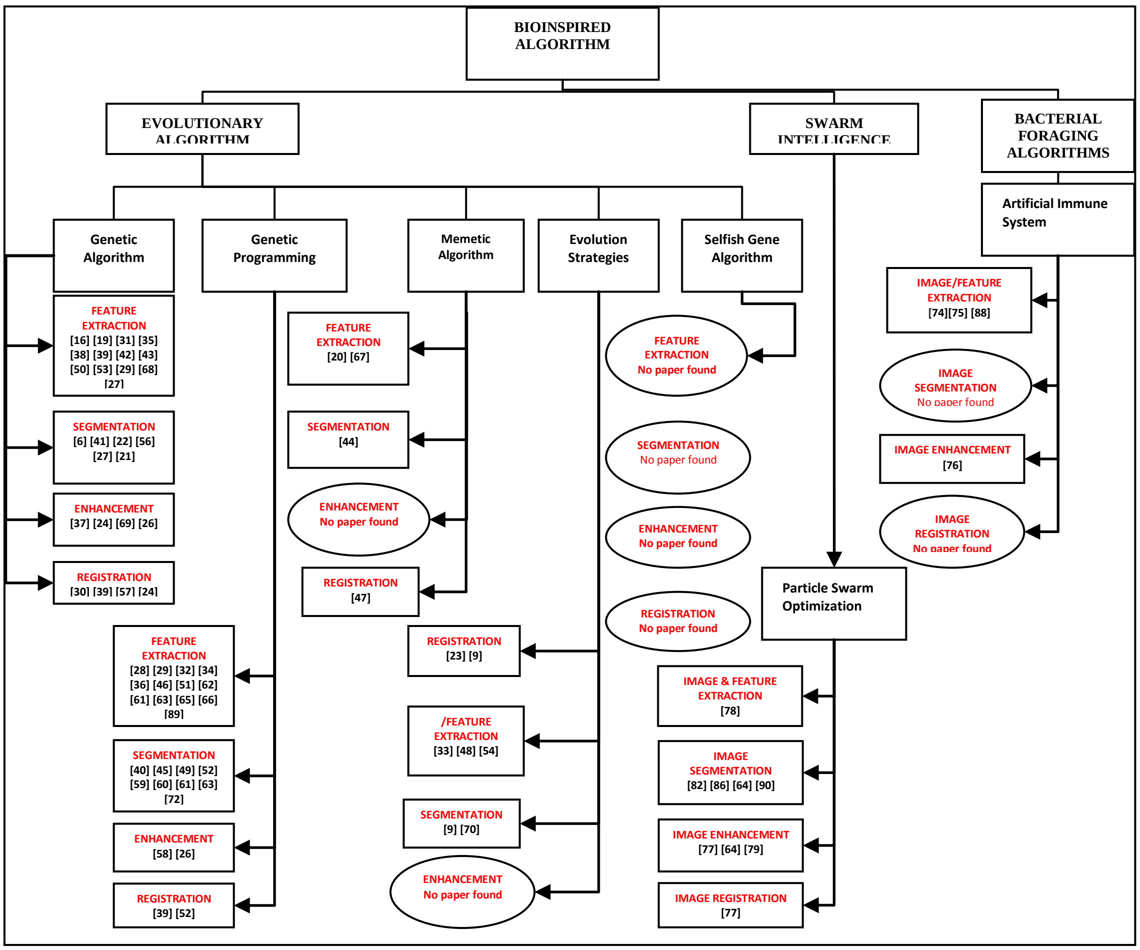

Fig 3. A hierarchical diagram showing the branch of Bio-inspired Algorithm in Image Processing field.

Table 3 shows the number of publications for each BIAs applied to the four image processing areas where a high number of publications are concentrated with the GA and GP. Only a small number of publications use MA, ES, PSO and AIS whereas SFGA has no publication.

Table 3. Number of publications for each BIAs sorted by the image processing technique.

Bio-inspired algorithm / Image application	GA	SFGA	MA	GP	ES	PSO	AIS
Image segmentation	9	0	1	9	2	4	0
Image Extraction / Feature extraction	13	0	2	14	3	1	2
Image Registration	4	0	1	2	2	1	0
Image Enhancement	4	0	0	2	0	3	1
Total	30	0	4	27	7	9	3

4.0 Conclusion and recommendation

This paper presents a bird's of eye view of BIAs techniques in image processing by identifying and analyzing approximately papers related to image processing. Out of a total of 130 papers (1995 to 2010), only 80 papers are found using BIAs techniques in image processing. It is also found that since 1995 to 2010, an exponential trend is observed which involved the research of BIAs for image processing techniques. The image processing techniques that employed BIAs are for the area of image and feature extraction (47%), segmentation (31%), enhancement (13%) and registration (9%). The Hierarchical diagram shows the BIAs techniques involved in image processing are the Genetic Programming, Artificial Immune System, Evolution Strategies, Genetic Algorithm, Swarm Intelligence and Memetic Algorithm. New BIAs algorithm such as Selfish Gene Algorithm should be explored as there is no literature yet to be found. The algorithm should work on image processing because of its' significant smaller CPU time and better robustness with the changes of the algorithm parameters and good convergence [101].

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