FEATURE OPTIMIZATION TECHNIQUES IN IMAGE CLASSIFICATION : A REVIEW

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Abstract - This paper has been written with the objective of studying and understanding the various feature optimization techniques in the field of image processing. Feature optimization is essential for reducing the number of input variables to in turn reduce the computational cost and to improve the performance of the model. In image processing, there exist a vast number of different optimization techniques ranging from heavily mathematical techniques to heuristic methods. This project deals with the discussion of six feature optimization techniques and their comparison. These techniques include Genetic Algorithm, Ant Colony Optimization, Particle Swarm Optimization, Cuckoo Search and Artificial Bee Colony Algorithm. Mainly, the paper aims to discuss the aforementioned algorithms stating their advantages, disadvantages and applications.

Keywords - Algorithm, Feature Extraction, Optimization, Population, Solution

I. INTRODUCTION

Image processing and analysis is a vast and important field of research given that the quantity of digital images is growing exponentially over time. Image processing is a technique used to get the digital form of an image in order to subject it to certain operations to procure valuable information from it or enhance it. Image processing allows us to improve image quality, enhance relevant information, simplify data and obtain more information about the image.

Feature selection or feature optimization is an important pre-processing step in image processing which aims at identifying relevant features and removing irrelevant or redundant features from a given image [1]. It is a technique of dimensionality reduction which commonly finds use in the processes involving data mining and enables irrelevant/redundant features to be omitted while maintaining the underlying relevant information. Therefore, data transmission is less and mining of data becomes more efficient. Feature selection is a significant topic in fields of the likes of machine learning [1]. It is capable of removing the irrelevant noisy features and thereby improve data returned and the system performance. These factors make feature optimization an essential and continuously evolving research area.

Feature selection allows an automatic selection of attributes in an image that are most relevant to the predictive modeling problem. Once features are selected, those that are essential in providing information about the image are selected and this procedure is feature optimization. Several techniques are employed to carry out feature optimization like Genetic Algorithm, Ant Colony Optimization, Particle Swarm Optimization, Cuckoo Search Algorithm, Artificial Bee Colony Algorithm, Firefly Algorithm, Hill Climbing, Iterated Local Search, Differential Evolution, multi swarm PSO among others [2], [3], [4], [5], [6], [7], [8], [9], [10], [11].

II. FEATURE OPTIMIZATION TECHNIQUES

A. Genetic Algorithm

Genetic Algorithm (GA) copies the natural process of evolution and produces an optimized result [2]. Here, GA is used for the purpose of feature selection to be used for a particular classifier. First step in GA is random population initialization. Binary format is the preferred format for initialization. Since it is an iterative algorithm, the number of iterations is defined by the value of fitness function, which is maximized or minimized according to the concerned procedure. Hence, crossover and mutation are performed in accordance with the value of the fitness function. GA keeps repeating these steps until a desired value is obtained.

Initialization happens when the initial population is generated randomly which allows the entire range of possible solutions called the search space.

New population is generated by two candidates who are selected in each iteration. This is based on the 'survival of the fittest' theory by Darwin [12]. Candidates having higher fitness value are accepted and those having a lower value are rejected. Selection can be done by various methods like Roulette Wheel Selection, elitism, rank and tournament selection [13]. Crossover or recombination is a genetic operator which creates off springs from parents i.e., new solutions. Types of crossover include one point

crossover, two-point crossover and three-point crossover.

In GA, particular bits are flipped for diversity. This happens on the basis of mutation probability [14]. A random number is generated between 0 and 1 and if its value is lower than mutation probability then mutation is performed, else not [14]. Types of mutation include Bit string, Flip bit, Boundary (the bit to be flipped is replaced by a number from either upper bound or lower bound), and Uniform (the bit to be flipped is replaced by a uniform number selected between upper bound and lower bound).

There is a stopping criterion or a limit on the number of iterations, whichever is achieved first terminates the process.

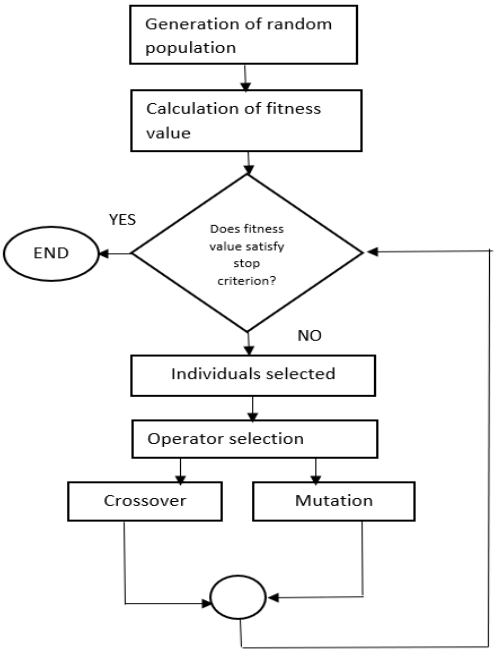


Fig.1 GA Flowchart

B. Ant Colony Optimization

Ant Colony Optimization (ACO) algorithm is essentially a probability-based method which is used for resolving optimization problems [3]. It can be implemented to find optimal paths with the use of graphs.

In the natural world, ants wander in random directions, along random paths in search of food. Once they find food, they go back to the colony while releasing pheromone trails along the path [15]. When other ants stumble upon such a pheromone covered path, they are more likely to follow the trail instead of travelling at random. If the ants eventually find food at the end of the path, they keep going along this trail thus strengthening it. Simulated ants are made to mirror this behavior and travel around graphs which represent the problem. The strength of the pheromone trail reduces with time due to evaporation [15]. The pheromones have more time to evaporate depending on how long it takes for ants to travel along the path and back again. Pheromone evaporation does not have a major role to play in natural ant colony behavior, however it is of utmost importance in artificial systems.

If the path is short, it gets travelled more frequently and therefore exhibits a higher pheromone density as compared to a longer path. Convergence to a locally optimal solution is avoided due to this phenomenon of pheromone evaporation. In the absence of pheromone evaporation, the initial paths chosen would be more appealing to the following ants which would lead to a constrained solution space.

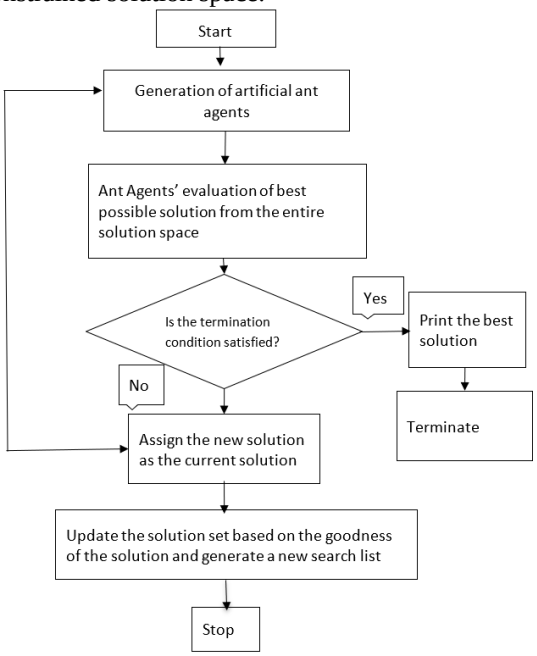


Fig.2 ACO Flowchart

In this algorithm the shortest path in a graph between two points A and B is constructed by the combination of multiple paths. ACO algorithms are population-based metaheuristics wherein ants mark the best solution and take account of previous markings to optimise their search.

C. Particle Swarm Optimization (PSO)

This novel technique is a stochastic search algorithm based on population. Swarm behavior (example: bird flocking, schooling in nature) inspires this optimization algorithm hence it's based on the natural communicative tendency within a group to share respective knowledge possessed by each member resulting from the migration of a bird or insect swarm to search space in order to look for food [16]. Even though all the birds don't know the exact coordinates of the food but due to the process of natural group communication, if any particle (term used for member) can find a fruitful path to be followed, the remaining members will adopt this method as happens in natural social behavior.

In this algorithm, the entire population is termed 'swarm'. The particles move in the search space of an optimization problem. Position of a particle represents a potential solution to the problem of optimization at hand.

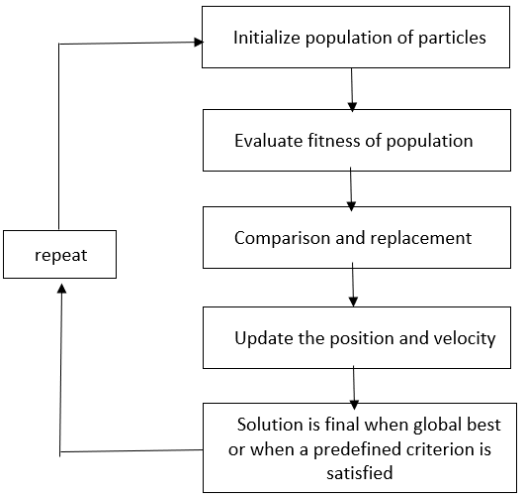


Fig.3 PSO Flowchart

The particles are passed around according to a few basic formulas in the search space. The motion of these particles in the search space is driven by the location(s) that they have the best knowledge of as well as the location that is in the knowledge of the swarm as a whole. As soon as a new enhanced location is found, they will then direct the swarm's motion. The method is replicated over and over again and we hope that an effective solution will finally be discovered by doing so.

D. Cuckoo Search Algorithm

In the Cuckoo search algorithm (CSA), certain cuckoo species act parasitically when they lay eggs in the nests that don't belong to them (i.e., of other species) and the birds, whose nests are used, become hosts [5]. Cuckoos have an active reproduction strategy involving the female laying her fertilized eggs in another species' nest so that her brood is unwittingly raised by the surrogate parents [17].

Cuckoo search (CS) is an optimization algorithm focused on the species of cuckoo which lays eggs in the nests of birds of another specie(s) (finding a value x such that f(x) is as small (or as big as possible) (of other species) [5]. The optimal solutions that CS has obtained are much better than the best solutions that an effective particle swarm optimizer has obtained.

CSA is governed by three rules which are: each cuckoo dumps the single egg it lays at a randomly selected nest, the nests harbouring the best quality eggs will be carried on to the next generation, the number of harbour nests (or host) is set, and each harbour is likely to find an unrelated egg randomly generated by P_i ($P_i \in (0, 1)$). If the P_i likelihood is greater than the P_a switching parameter, then the host will discard its nest, resulting in the creation of a new nest in a new location.

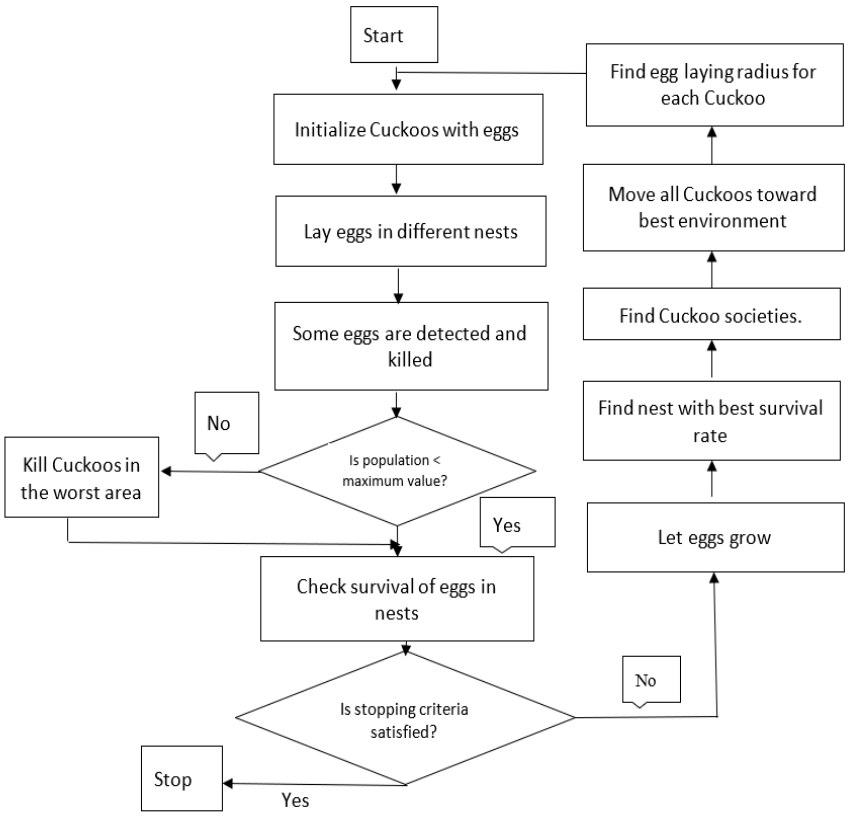


Fig.4 CSA Flowchart

E. Artificial Bee Colony (ABC) Algorithm

Tereshko and Loengarov, in 2005, proposed a model on foraging associated with colonies of honey bees which forms the basis of ABC [18]. The algorithm consists of three basic components: working bees, unemployed bees (both of which are foragers) and food sources [18]. The first two components, working and unemployed foraging bees, look closely to their hive for rich sources of food, which is the third component. The model also describes two leading behavioral modes that are needed for self-organizing and collective intelligence: the recruitment of foragers to rich food sources, resulting in positive feedback and negative feedback from foragers leaving poor sources. An artificial bee colony of foragers checks for the rich sources of food (which are artificial) which is analogous to good outcomes.

The first step in the application of ABC is the translation of the optimization problem considered to a quest to find the best vector of parameters which reduces an objective function to its lowest possible value. The bees then discover a considerable number of initial solutions pointing in a suitable direction at random and then strengthen them iteratively by using the strategies: passing through a neighbor search mechanism to move towards better solutions while abandoning poor solutions.

In ABC, there are three classes of bees in the colony of artificial bees: bees associated with specific food sources (called employed), bees who watch employed bees dance inside the hive to select a food source (called onlookers), and bees randomly looking for food sources (called scouts). Unemployed bees are named both onlookers and scouts. All food source locations are initially found by scout bees. Then, working bees and onlooker bees continuously exploit the nectar from food sources, so this continued exploitation exhausts the sources eventually. Then, in search of more food sources, the employed bee that exploited the depleted food source again becomes a scout bee. The working bee whose food supply has been depleted, in other words, now starts looking randomly for food sources (scout bee).

Here, the area where a food source is located is analogous to a possible solution and the quantity of nectar in a particular source of food to the solution's fitness. The count of working foragers is same as the count of food sources located (called solutions) as one working (or employed) forager and one food source are related exclusively.

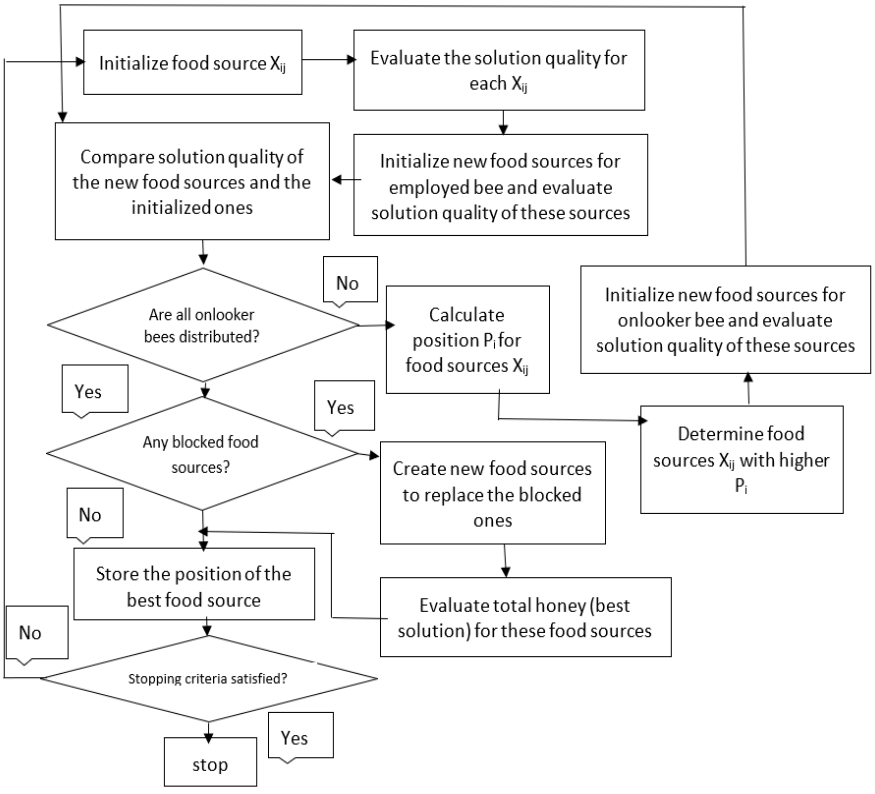


Fig.5 ABC Flowchart

III. COMPARISON TABLE

OPTIMIZATION TECHNIQUE	ADVANTAGES	DISADVANTAGES
Genetic Algorithm [2].	1.Supports multi objective optimization 2.Searches from a population of points, not a single point 3.Uses objective function, not derivatives	1.Computationally time consuming 2.Difficult to design objective function
Ant Colony Optimization [3].	1.Enables parallel search in a population 2.Enables rapid discovery of good solutions 3.Adaptable to changes like new distance	1.Probability distribution might change with every iteration 2.Difficult theoretical analysis and is more experimental 3.Uncertain time of convergence
Particle Swarm Optimization [4].	1.Quick and easy to implement. 2.Have a few adjustment parameters 3.The PSO calculation is quick. 4.Takes less time for computation	1. Defining initial design parameters could be problematic 2.PSO suffers from partial optimism, which degrades its velocity and direction control. 3.Non-coordinate system exiting problems
Artificial Bee Colony Algorithm [6].	1.Very robust 2.Strong convergence 3.High flexibility 4.Employs fewer control parameters which makes it a better performer	1.Converges prematurely in the later search period 2.Sometimes, optimal value accuracy falls short of the required.
Cuckoo Search Algorithm [5].	1.Easy to implement 2.Other swarm-based algorithms can also be hybridized [21]. 3.It supports the search capabilities of local and global	1.Quickly falls into the locally optimal solution 2.Slow convergence rate

Table I. Comparison of the Techniques

IV. CONCLUSION

Genetic Algorithm (GA) is a technique which sees widespread application in image processing [2]. It can be applied to optimize features of images from any field while the rest of the techniques perform at their best when applied to certain type of images (like Ant Colony Optimization finds limited use in telecommunications and traffic regulation) [3]. Genetic Algorithm might be a time-consuming technique but it produces very valuable and close to accurate results in comparison with any other technique since it searched from a population of points. Due to this unique feature of searching from a population of points and not a single point, Genetic Algorithm does not converge prematurely like it happens with Cuckoo Search Algorithm and Artificial Bee Colony Algorithm [2], [5], [6]. Genetic Algorithm takes much computational time to produce results from a huge population of points, which serves as a disadvantage against other techniques that have been discussed, especially Particle Swarm Optimization and Ant Colony Optimization [2], [3], [4].

Apart from Genetic Algorithm, the discussed techniques rely on relatively fewer complex mechanisms to optimize image features. Genetic Algorithm relies on an objective function which is difficult to devise [2]. However, this hurdle, once overcome, produces the best results among all other techniques. Moreover, initial parameters can be difficult to decide in Particle Swarm Optimization as well [4].

While Genetic Algorithm might produce the best results, Artificial Bee Colony Algorithm and Cuckoo Search Algorithm are also good performers, especially with the advantage of high flexibility and less complexity; the latter is a key feature of the Artificial Bee Colony Algorithm [2], [5], [6]. Cuckoo Search can be hybridized with other swarm algorithms- a feature which Genetic Algorithm fails to offer [2], [5].

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