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A Review: A Comparative Analysis on the Biometric Optimization Techniques

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Abstract:
A review paper on different types of population based Biometric optimization techniques. Now days, it's required to determine the optimal time and population size of the biometrics along with the reduction of the loss, improvement of Voltage Profile and reliability at lowest cost with the growing popularity. Increase in desirability of the optimization techniques are increasing with the demand of electrical energy, reducing the system cost, increasing the population size and reliability of the system, convergence is guaranteed etc. Thus we use different types of optimization techniques such as Genetic Algorithm, BFO, PSO, Ant Colony Optimization etc. These biometric optimization techniques are evaluated on the basis of transition time, population size, number of iteration, cost, FAR, FRR, EER, ACCURACY etc.

Keywords: *FAR, FRR, EER, Accuracy, Genetic Algorithm, Bacterial Foraging Optimization, Particle Swarm Optimization, Ant Colony Optimization*

1. Introduction

Artificial intelligence (AI) is the intelligence exhibited by machines [17]. It is a tool which has the capability of capturing the fluidity and adaptability of human information processing. As a result of development of optimization algorithms there is a great breakthrough in understanding of cognition (process of acquiring knowledge and understanding through thought, experience, and the senses).

"Biometrics" is derived from the Greek words "bio" means life and "metric" means measure. A person's unique physical and behavioural characteristics are measured and analysed by biometrics. The theory behind fusion is not limited to biometrics: biometric based decisions are a special case of classification in the field of statistical pattern recognition, and biometric fusion analogously can be considered a special case of combining multiple classifiers in pattern recognition [18].

Increase in desirability of the optimization techniques are increasing with the demand of electrical energy, reducing the system cost, increasing the population size and reliability of the system, convergence is guaranteed etc. Practical applications of using this technique in biometrics will help in forensics, prevents unauthorised access to ATM, cell phones, transaction done through electronic banking, can replace keys with keyless entry device etc. The optimization techniques can be rated or calculated by FAR, FRR and ACCURACY. The paper is presented as follows: Basic introduction on the aim of this review paper Section 2 literature of biometrics optimization techniques is illustrated, in Section 3a brief idea about the optimization techniques, in section 4 the review of related work, different optimization techniques are presented. Conclusions are presented in the last section of the paper.

2. Literature Review

- In 2005, K. Veeramachaneni, L. A. Osadciw;P. K. Varshney [1] proposed that the decision fusion rules are adapted to meet the varying system needs by PSO. To change security needs as well as user needs, the adaptive multimodal biometric management (AMBM) allows reacting in pseudo real time. To reflect the security and user needs of the system error weights were modified. The AMBM algorithm selects the fusion rule and sensor operating points to optimize system performance in terms of accuracy. This research does not consider the case when any of the individual sensor operating point is FAR=1, FRR=0. The results reported indicated that the search space has been limited to only few monotonic rules which can inherently prevent other optimum rules from being selected.
- In 2003, Kalyan K. Veeramachaneni; Lisa A. Osadciw; Pramod K. Varshney [2], proposed an algorithm called Adaptive Multimodal Biometric Fusion Algorithm(AMBF), which is a combination of Bayesian decision fusion and particle swarm optimization. To fuse decisions received from multiple biometric sensors a Bayesian framework is implemented which also formalizes the design of a system that can adaptively increase or reduce the security level. PSO searches the decision and sensor operating points (i.e. thresholds) space to achieve the desired security level. The optimization function aims to minimize the error in a Bayesian decision fusion. The result emerged an adaptive and dynamic fusion design. The solutions that meet the system performance criteria may not be intuitive solutions. The results obtained by running the swarm with CFA= 1.9 and CFA= 1.8, respectively. The two cases

with only a cost difference of 0.1 result in the swarm switching from an AND rule to an OR rule with very different sets of operating points. For the higher cost, the swarm converged to a final solution after 550 iterations. The results report indicated that the search space has been limited for the user to improve the quality of the fusion rules selected by the swarm and the transition time.

- In 2011Mathur U, Gill Sandeep S., Dr. Rattan Munish [11], Biometrics Eye images deteriorated by noise due speckle interferences for removal Homomorphic Wiener filtering is used after which Bacterial Foraging Optimization (BFO) is applied on filtered eye images which minimizes mean square errors between filter output image and original image. The Peak Signal to Noise Ratio (PSNR) of the image using BFO is much higher than that of the filtered images which improves the accuracy. For testing the images have been corrupted with speckle noise densities varied from 10% to 90% with increments of 10%. PSNR after BPO is around 88 db and PSNR after Homomorphism Wiener filtering is 70 db, the PSNR gain is 18 db. BFO technique gives enhancement of Peak Signal to Noise ratio which is better in terms of PSNR.
- In 2011, L. LATHA [9], Multimodal biometric system proposed that combining and accessing the scores of iris and palm print traits of a person at the matching score level. with the threshold value, the resulting scores are compared for decision making for accepting or rejecting the person. They proposed Ant Colony Optimization (ACO) technique for selecting the optimal threshold value. Results obtained using CASIA iris and palm print databases show that the application of ACO results in higher recognition rates and lower error rates. In particular max, sum and mean fusion methods give the best results in terms of the low EER 0.64% and high recognition rate 99.32%.
- In 1995, Kennedy J., and Eberhart R.C [3], proposed the relationships between particle swarm optimization PSO and both artificial life and genetic algorithms. The trained weights found by particle swarms sometimes generalize from a training set to a test set which are better than solutions found by gradient descent. A data set representing electroencephalogram spike waveforms and false positives, a back propagation NN achieved 89 percent correct on the test data. The particle swarm optimizer was able to train the network so as to achieve 92 percent correct. This algorithm belongs ideologically to that philosophical school that allows wisdom to emerge rather than trying to impose it, that emulates nature rather than trying to control it, and that seeks to make things simpler rather than more complex.
- In 1998, Shi Y. and Eberhart RC [4], proposed a new parameter, called inertia weight, into the original particle swarm optimizer. The PSO with the inertia weight in the range [0.9,1.2] on average has a bigger chance to find the global optimum. The inertia weight does not need to decrease from 1.4 to 0. A decrease from 1.4 to 0.5; will work better. They proposed that the inertia weight can be considered as a decreasing function of time instead of a fixed constant. Through a fuzzy system could be built to tune the inertia weight on line.
- In 2004, G. H. Omran [5], proposed an efficient dynamic clustering algorithm that can find the optimum number of clusters in a data set with minimum user interference that would minimize the quantization error and intra-cluster distances, and to maximize the inter-cluster distances while having quantization errors comparable to the other algorithms. To tackle the colour image quantization problem they used PSO-based approach. Although the parametric fitness function used by the PSO-approach contains multiple objectives, no special multi-objective optimization techniques have been used. In addition, incorporating spatial information into the PSO- based clustering algorithm (when used in image segmentation applications) needs to be investigated. The performance of different versions of PSO was investigated and the results suggest that algorithms that start with high diversity and then gradually go to low diversity perform better than other algorithms.
- In 2011 Rajasekhar Anguluri, Ajith Abraham and Vaclav Snasel [6], proposed a new hybrid algorithm combining the features of BFOA and Particle Swarm Optimization (PSO) for tuning a Fractional order speed controller in a Permanent Magnet Synchronous Motor (PMSM) Drive to overcome the delay in optimization and to further enhance the performance of BFO. A novel ABF-PSO algorithm is used for tuning a FOPI Speed controller for PMSM in electric drive mining truck. Percent overshoot, steady state error is very much improved in ABF-PSO tuned FOPI controller. The results report indicated that the search space has been limited on implementing FOPI controller for the sensor less PMSM drive.
- In 2012, Vipul Sharma, S.S.Pattnaik, Tanuj Garg [7] proposed that finite difference time domain method FDTD is used to simulate electric field values at given number of points in space and then GRN is used to predict the values at all possible points. BFOA has been used to optimize spread of GRN. This hybrid version of FDTD (BFO-FDTD) leads to faster convergence with high accuracy. They compared the electric field values obtained from conventional FDTD and BFO optimized GRN FDTD which converges to null value of mean square error up to tenth decimal point. Optimized value of spread constant obtained from BFO came out to be 0.3889.
- In 2012 Livjeet Kaur Mohinder Pal Joshi [8], proposed that PSO has been replaced by BFO for optimization. They analysed chemo tactic behaviour of bacteria by minimizing mathematical benchmark functions. Faster chemo tactic movement (i.e. larger step size) results in a wider search of given search space contrary to slower chemo tactic movement (i.e. smaller step size) which performs comparatively narrow or minute search. Depending on the nature of search space, bacteria can be made self-adaptive in deciding the value of the step size. Effect of cell to cell attractant and repellent can also be included. Limitation of taking small step size is that sometimes bacteria may get stuck into local optima thus it will not be able to reach at global optima for its entire life time.
- In 2013, Purneet Kaur [10] In biometrics, Genetic algorithm is used for the extraction of minutiae and neural network is used for the recognition of a fingerprint. Then morphological Image processing operations has applied for thinning the lines. Genetic Algorithm is used to find the best possibility for each discontinues segment in an image. Then Enhanced image has fed to NN (neural networks) based trained system to diagnose and match finger print with data set. GA give the best results in terms of the low EER and high recognition rate.

- In 2006, M. Dorigo et al. [12] proposed that the search procedure of ACO algorithms is solution construction by artificial ants and local search to improve the solutions constructed by the ants. Incremental local search is an approach that consists in re-optimizing partial solutions by a local search algorithm at regular intervals while constructing a complete solution. The ant colony optimization is said to solve the quadratic assignment problem although the results are negative. The incremental local search somehow destroys the behaviour of the ACO algorithm in its exploitation phase by not allowing it to generate solutions that are rather close to the restart-best or global-best solutions. Their results indicated that incremental local search could be useful for increasing the exploration in convergence situations of ACO algorithms although was not useful for QAP.
- In 2015, Mirzakhmet syzdykov, Madi uzbekov [13], proposed ant system simulation to produce feasible layouts in order to minimize the total unused area which produces non-slicing floor plan. The ant colony optimization (ACO) in VLSI design, defines the "interior" structure for a geometrical computation of module positions.The clustering method used to handle large amounts of data. This is not limited to the experiments when the list of constraints is extended as well as the list of semantic rules, for which the final placement rectangle's size and shape constraint satisfies. ACO modules can be arranged with no overlaps. If the number of artificial ants and number of outer iterations is increased that algorithm gives better results i.e. dead space for 25 iterations with 25 ants is 6.88% with run time of 16 seconds.These clusters at their finite hierarchy are modules representing the input data for the global algorithm.
- In 2006, Mohammad Hadi Afshar, H. Ketabchi, E. Rasa [14] proposed Continuous Ant Colony Optimization (CACO) algorithm for optimal reservoir operation, determining and setting a complete set of control parameters for saving the user from a tedious trial and error based approach to determine them The results indicated good performance for global minimization of continuous test functions. A normalized squared deviation of the releases from the required demands is considered as the fitness function and the results are presented and compared with the solution obtained by Non Linear Programming (NLP) and Discrete Ant Colony Optimization (DACO) models. The results of the mean best fitness value are Proposed CACO=32.32, PSOPC=32.44, GSPSO=52.83, LSPSO=347.42, CPSO=39.7 are evaluated which state that CACO algorithm are superior to those obtained from NLP and DACO models. Global optimal solutions can be reached more rapidly by self-adjusting the path searching behaviour of the ants according to objective values.
- In 2006, Jihad Jaam [25], In biometrics, the image is tested and verified using both Genetic algorithm and Hough procedure. Results states that GA give the best results in terms of the low EER and high recognition rate and provides accuracy of 99% while Hough procedure provides accuracy of 96%.
- In 2002, Christine Solnon [15], described ant colony optimization (ACO) met heuristic for solving constraint satisfaction problems (CSPs). The experiments with different values of P_{NOISE} ranging from 0.01 to0.1 ate evaluated of which the best results were obtained when p=0:07. Pheromone is used to learn the global desirability of a set of variable-value assignments and it is used as a heuristic for choosing values when constructing an assignment. The results state that ants alone without LS abilities are able to solve hard instances, although they are rather slow at finding solutions which used the MCH for LS. Ant-Solver requires more time to converge, but it actually solves many more instances. Therefore, the combination of RWLS with Ant-Solver could allow one to take advantage of both features. A disadvantage of the Ant-Solver is that; it may be less efficient than specialized algorithms. To handle such global constraints, translate them into an equivalent set of simpler constraints and then use Ant-Solver.
- In 2012, Rahul Putha, Luca Quadrifoglio & Emily Zechman [16],proposed to solve the oversaturated network traffic signal coordination problem using the ACO algorithm. The ACO algorithm finds intelligent timing plans which take care of dissipation of queues and removal of block ages as opposed to the sole cost minimization usually performed for under-saturation conditions. The results are compared with solutions obtained using the genetic algorithm (GA), traditionally employed to solve oversaturated conditions. ACO algorithms implementation is suggested to reduce the overall execution time allowing the opportunity to solve real-time signal control systems. Statistical analysis showed that ACO yielded better results when compared to GA for cases that utilized a higher number of model executions. The drawback a using the ACO algorithm is parallel-computing approach.ACO was able to identify increasingly more fitness solutions as the number of executions was increased, while the GA identified similarly good solutions for all settings.

3. Biometric OptimizationTechniques

3.1. Bacterial Foraging Optimization Algorithm (BFOA)

The animals with poor foraging strategies are eliminated and successful ones tend to propagate thus foraging is crucial in natural selection. The foraging strategy is headed by four processes namely Chemo taxis, Swarming, Reproduction, Elimination-Dispersal.

3.1.1. Chemo Taxis

The E. Coli bacteria by a series of tumbles moves through the environment and runs,avoiding the noxious substances and getting closer to food patch areasthrough two processes namely swimming and tumbling called Chemotaxis. If it moves in a predefined direction called swimming and tumbling if moving in an altogether different direction. Let j be the index of Chemo tactic step, k be the reproduction step and l be the elimination dispersal event. Let Θi (j+1, k, l) representsthe position of i^{th} bacteria at j^{th} chemo tactic step, k^{th} reproduction step and l^{th} elimination dispersal event. C(i) be the size of the step. The position of the bacteria in the next chemo tactic step after a tumble is given by:

$$\Theta^i (j+1, k, l) = \Theta^i (j, k, l) + C(i) * \Delta(i)/\mathrm{sqrt}(\Delta Ti * \Delta(i)) \quad (1)$$

Where Δ indicates a vector in the random direction whose elementslie in [-1, 1]

The bacteria will continue to swim to the same direction for the specified steps or until the health degrades, if the health of the bacteria improves after the tumble.

3.1.2. Swarming

Bacteria exhibits swarm behaviour i.e. healthy bacteria try to attract other bacteria so that together rapidly they reach the desired location. Bacteria congregate into groups and move as concentric patterns with high bacterial density which is the effect of swarming. Mathematically swarming behaviour can be modelled as-

Jcc (Θ, p (j, k, l) =Jccni=1(Θ,Θi(j,k,l)=[−dattractexp(−WattractΘm−Θmini=1Si=12)]+[−hrepellentexp(−WrepellantΘm−Θmini=1Si=1 (2)

3.1.3. Reproduction

If the population members have had sufficient nutrients they will reproduce and the least healthy bacteria will die. The healthier half of the population replaces with the other half of bacteria which gets eliminated, owing to their poorer foraging abilities. This makes the population of bacteria constant in the evolution process.

3.1.4. Elimination and Dispersal

A sudden unforeseen event may drastically alter the evolution and may cause the elimination and/or dispersion to a new environment. Elimination and dispersal helps in reducing the behaviour of stagnation i.e. being trapped in a premature solution point or local optima.

3.2. Ant Colony Optimization (ACO)

The ACO algorithm is derived from 3 activities.

3.2.1.The initialization of the pheromone trail.

3.2.2.A complete solution to the problem is constructed by each ANT according to a probabilistic state transition rule. The probabilistic state transition rule depends on the state of the pheromone.

3.3.3.The quantity of pheromone is updated in the third step; a pheromone updating rule is applied in two phases. An evaporation phase is the first phase where a fraction of the pheromone evaporates, and a reinforcement phase on path with high quality solutions increases the amount of pheromone.

These processes are iterated until they reach a stopping criterion.

In solving the optimization problem these principles are proposed to translate into a computational procedure. Different ways have been proposed to translate the above principles into a computational procedure. Nodes probabilistically are selected by the ants basedon the amount of pheromone at each node. Higher probability resulted in the higher concentrations of the pheromone on a node result that the node will be selected as a partof the solution. The value of a decision variable is

G =(Gmin−interval size)+(node number∗interval size) (3)

Where:

G min = minimum value for the green time (the variables used in the signal timing problem)

G = the value of the decision variable.

3.3. Particle Swarm Optimization (PSO)

With the motivation of the social behaviour of organisms, Kennedy and Eberhart introduced the PSO method. Particles change their states with time can fly around in a multidimensional search space. Every particle with the experience of its neighbouring particles adjusts its states according to its own experience which the particle would make the best position for itself and for its neighbours. PSO provides a population based search procedure. A particle with its neighbouring and its history experiences defines the swarm direction. Let x and v denote a particle position and its velocity in a search space. Therefore, the i^{th} particle in the d dimensional space is showed as xi=(xi1+xi2.......xid). The best previous position of the i^{th} particle is recorded and represented as pbest i= (pbesti1pbesti2, ...pbestid) and the velocity is represented as vi=(vi1,vi2,...,vid). Using the current velocity in distance from pbestid to gbestd (the best particle among all the particles in the group) we can calculate the modified velocity and position.

$Vid^{(t+1)}=w.Vid^{t}+C1*rand()*(pbestid-Xid^{t})+C2*rand()*(gbestid-Xid^{t})$ (4)

$Xid^{t+1}=Xid^{t}+Vid^{t+1}$ (5)

Where:

i= 1,2.....n

d = 1,2......m

n = number of particles in a group.

m = number of members in a particle.

t = pointer of iterations.

w = inertia weight factor.

C1 and C2 = uniform random values in the range [0,1].

$Vi^{(t)}$ = velocity of the particle i at iteration t
$Xi^{(t)}$ = position of particle i at iteration t
$vdmin \le vid^{(t)} \le vdmax$ (6)
The parameter Vmax determines the resolution, or fitness, with which regions are to be searched between the present position and the target position. If Vmax too high, particles might fly past good solutions. If Vmax is too small, particles may not explore sufficiently beyond local solutions. The inertia weight w is set according to the following equation:
$W=Wmax*((Wmax-Wmin))/(itermax))*iter$ (7)
where:
Wmax = initial weight,
Wmin = final weight,
iter = current iteration number,
itermax = maximum iteration number.

3.4. Genetic Algorithm (GA)
Constrained and unconstrained optimization problems are solved by GA, that are based on natural selection, the process that drives biological evolution providing best solution without worrying about local minima and just relying on an elite preservation strategy. The GA, at each and every step selects individuals at random from the current population to be parents and uses them to produce the children for the next generation which follows two main types of rules:

3.4.1. Selection rules select the individuals, called parents that contribute to the population at the next generation.

3.4.2. Reproduction is the step used to generate a second generation population of solutions from those selected through genetic operators: crossover (also called recombination), and/or mutation. A-Crossover rules combine two parents to form children for the next generation; B-Mutation rules apply random changes to individual parents to form children.

The procedure used for generating simpleform of the genetic algorithms is:

3.4.2.1.Generate random population of n chromosomes (suitable solutions for the problem)
w_0i, i = (w_1, w_2) i = 1...N {where N: size of population} (8)
3.4.2.2. Fitness function f(x) of each chromosome x in the population is used for evaluation
Equal Error Rate, EER ($U = w_1x_1 + w_2x_2$) (9)
3.4.2.3. These steps are repeated for creation of new population.

4. Review of Case Study

- Patricia [19] In biometrics, PSO has no evolution (genetic) operators such as mutation and crossover. Particles update themselves with the internal velocity. There is no feature selection in PSO. After executing GA with different number of variables using a fuzzy system in decision making for biometrics, the average value of 9.42E-04 and that of PSO is 5.34E-11.
- Rechu Sharma [20] The recognition system in biometrics is evaluated on FAR and FRR rate. These rates are deceased with the increased in the system performance on the biometric data set using GA over PSO. FAR=0.065%, ACCURACY=93.41% AND FRR=0.00032% in GA and FAR=0.095%, ACCURACY=90.36% AND FRR=0.0010% for PSO.
- Jihad Jaam [22], proposed that in biometrics, the image is tested and verified using both Genetic algorithm and Hough procedure. Results states that GA give the best results in terms of the low EER and high recognition rate and provides accuracy of 99% while Hough procedure provides accuracy of 96%.
- lir Juniku [23] proposed that transient responses for BFO, raising time 0.73 peak time 1.75 while that of PSO is raising time 0.83 peak time 1.97 which concluded that the PSO algorithm is more efficient and provides a better tuning of the process of intelligent algorithms. It provides the best value (minimum value) of the cost function. PSO algorithm has simpler computing architecture and a faster algorithm in computing time than BFO algorithm.
- Tobias Scheidat [16] state that an optimization strategy has been used for biometric parameters using genetic algorithm (GA) for all test databases, new acquired BioGINA database and the databases of the past, an improvement was reached. To calculate a new parameter set and test the BioGINA, Genetic optimizer had been used as a training set for public FVC databases of the years 2000, 2002 and 2004. For BioGINA an improvement of 25% was reached in accuracy and equal error rate was obtained of 40% for database 1 of the FVC 2000.
- Cenys [17] authentication and identity management problems are now solved by Biometric authentication systems. The full sorting method reliability 92% is sufficient while for GA reliability is around 96% expressed in biometric authentication systems. Detection rates that are achieved still need to be improved by optimizing genetic algorithm parameters. The time consumption of full sorting is 220 sec while that of GA is 25 sec. Thus Genetic algorithms applications such as handprint search and recognition, time consumption decreases to almost 10 times compared to full sorting method.
- Mehdi Hosseinzadeh Aghdam [18] in 2012Both ACO-based and GA-based algorithms reduces the dimensionality of feature space. A percentage of Selected features for GA is 32% and ACO is 20%. The EER of GA is 4.96 and that of ACO is 4.318which states that GA is more efficient than ACO. ACO is having a memory while GA does not. GA evaluates on the basis of present changes and parameters or features selected.
- Juicy Ray [21] When Feature Selection in biometrics is done through PSO, Training Time = 161.86 sec and Recognition Rate = 93.7% but for BFO, Training Time = 257.13 sec and Recognition Rate = 95.14%. The number features required by BFO are less than that required for recognition using PSO as the average recognition rate of BFO is better than that of PSO-based feature selection

but computational time, PSO-based selection algorithm takes less training time than the BFO-based. BFO is computationally expensive than PSO.

5. Conclusion

In this Paper a Comparative Analysis was made on the biometric optimization technique, withthe increasing demand of electrical energy, reducing the system cost, increasing the population size and reliability of the system, convergence is guaranteed etc. using different population based artificial intelligence techniques. After the relevant case study, we can say that the different methods used for this optimization techniques are GA,PSO,BFO,Ant Colony Optimization etc. GA has a fitness function through which we can assign the parameters threshold value and can select the large number of parameters on basis of which the biometric authentication system should be evaluated. GA can also handle the great population size in biometrics than compared to ACO and PSO.GA provides better performancein biometrics but as GA can handle large population size and parameters for which the transition time increases than that of ACO and PSO. In biometrics the EER is high for GA. PSO cannot work on scattering of the particles and its population size is limited upto 30 to 40 iterations while GA works better in both the cases. ACO is having a memory in genetic population of biometrics while GA does not. GA evaluates on the basis of present changes and parameters or features selected in the genetic population. PSO algorithm has simpler computing architecture and a faster algorithm in computing time than BFO algorithm.

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