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Diego Oliva
Salvador Hinojosa *Editors*

Applications of Hybrid Metaheuristic Algorithms for Image Processing

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Preface

Since the use of digital images is a part of our life, it is necessary to have accurate algorithms that permit us to analyze the objects contained in the scene according to a specific application. The computer vision systems have different phases, but one of the main tasks is segmentation, where the objects are cataloged according to the intensity levels of the pixels. However, this is not the only important step in such system, the classification, shape analysis, and feature extraction are some of the tasks that represent challenges in image processing.

Currently, metaheuristic algorithms (MA) are considered important optimization tools commonly used to solve complex problems. These kinds of methods consist of two main processes exploration and exploitation. In such phases, the algorithms employ different operators and rules to search the optimal solutions. Here, it is important to mention that metaheuristics are commonly inspired by natural behaviors that define its classification. For example, the family of algorithms that employs operators inspired in the natural selection is called evolutionary, meanwhile the algorithms that employ a population classified as swarm methods. Metaheuristic approaches are not perfect, and their drawbacks as slow convergence or when they provide suboptimal solutions affect their performance and cannot be considered for all the problems. A common alternative for addressing the failures of optimization algorithms is the hybridization because it permits the combination of strategies for exploring complex search spaces.

The hybridization can take two forms: sequential use of algorithms and the replacement of operators. In the first case, two MA run in sequence to firstly explore with an algorithm and then perform exploitation on the later; however, this approach can significantly increase the number of iterations required to converge. In the second case, the operators of two or more algorithms which are mixed together provide a better balance between the intensification and diversification of the solutions without increasing the number of iterations.

This book is focused on the theory and application of MA for the segmentation of images from different sources. In this sense, topics are selected based on their importance and complexity in this field—for example, the analysis of medical images of the segmentation of thermal images for security implementation.

This book has been structured so that each chapter can be read independently from the others. This book is divided into three parts that contain chapters with similar characteristics.

The first part is related to hybrid metaheuristics and image processing. Here, the reader could find chapters related to thermal, hyperspectral, and remote sensing images. Moreover, some hybrid approaches permit, for example, to analyze different features as the texture in the digital images.

The second part is addressed other problems in image processing with hybrid MA, for example, object recognition by using template matching, the use of clustering for morphological operations, or the estimation of homography. This section also includes the use of deep learning and a literature review of a well-known MA.

One of the most important uses of digital images is medicine; for that reason, the third part encapsulates different chapters related to health. Here, MA are used and hybridized for tasks as magnetic resonance analysis, detection of anomalies in mammograms, Parkinson's disease among others. The reader will be highly interested because the mixture of methods permits to explore machine learning applications included adversarial networks.

The material presented in this book is essentially directed for undergraduate and postgraduate students of Science, Engineering, or Computational Mathematics. It can be appropriate for courses such as artificial intelligence, evolutionary computation, and computational intelligence. Likewise, the material can be useful for researches from evolutionary computation and artificial intelligence communities.

Finally, it necessary to mention that this book is a small piece in the puzzles of image processing and optimization. We would like to encourage the reader to explore and expand the knowledge in order to create their implementations according to their necessities.

Guadalajara, Mexico
November 2019

Diego Oliva
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Hybrid Metaheuristics and Image Segmentation

Ethnic Characterization in Amalgamated People for Airport Security Using a Repository of Images and Pigeon-Inspired Optimization (PIO) Algorithm for the Improvement of Their Results

Alberto Ochoa-Zezzatti, José Mejía, Roberto Contreras-Masse, Erwin Martínez and Andrés Hernández

Abstract Nowadays, the latent danger that there is a terrorist attack in an airport anywhere in the world is a matter of first importance, that is why biometrics plays a vital role in our daily life—In our case it can determine the Facial characteristics of an individual, including their ethnicity. Given that this type of intelligent applications that detect and determine the facial attributes of people is highly safe and convenient, our society makes use of this technology almost everywhere, from the surveillance in the airport, as has been mentioned, to smart homes. in general in any aspect related to a smart city. In comparison with other biometric solutions, facial recognition produces greater advantages, since it does not require interaction or the permission of the subject. From this point of view, it represents a fast and effective way to increase our level of security, especially in open and crowded places. Automated facial recognition is a modern concept, and novel research related to image analysis. It was born in the 1960s and is still in permanent development. In 2006, the project "Facial Recognition Grand Challenge" (FRGC) evaluated the facial recognition algorithms available at that time. Tests with 3D scanners, high-quality images, and iris photographs. The FRGC showed that the algorithms available at that time were 10 times more accurate than those of 2002 and 100 better than those of 1995. Some recognition methods were able to overcome humans in face recognition and could even distinguish between twins identical In our case and using a novel algorithm called Pigeon-Inspired Optimization (PIO) Algorithm.

Keywords Pigeon-inspired optimization algorithm · Pattern recognition · Decision support system

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1 Introduction

Some time ago, after an audit by the Federal Aviation Administration of the United States (FAA), within the framework of the International Civil Aviation Organization (ICAO), Mexican aviation was degraded from Level One to Level Two. This audit does not qualify the operating companies, but the authority responsible for the airspace, in this case, the General Administration of Civil Aeronautics (DGAC), dependent on the Ministry of Communications and Transportation (SCT). While the degradation persisted, the effects were, among others: Mexican airlines could not carry out codeshare flights, nor acquire more planes, nor create new routes to the United States. 162 days later (and an investment around 50–60 million pesos), the SCT reports that Level One has been recovered. Independently of this and in spite of the fact that, at the time, it was said that "the decrease in the Level had no relation with safety standards", we recently came across the news that flight crew of a national airline were captured in Spain, by trafficking drugs, after having cheated security at the International Airport of Mexico City (AICM). A forum was held where, among other topics, various proposals and studies related to airport security were presented. The National Polytechnic Institute (IPN) presented a study that can help us illustrate the problem.

IPN study reports that in Mexico there are 85 airports, of which 59 are international and 26 are national. 74,920,348 passengers and 768,526 tons of cargo are transported through the Mexican airport system, of which 68.19% of the passengers and 81.44% of the cargo flow through the four main airports (Mexico City, Cancún, Guadalajara, Monterrey). Regarding security problems, with data from the Preventive Federal Police (PFP) and Aeromexico, at Mexico City airport the frequency of crimes is grouped as follows: weapons (0.8%), contraband (0.4%), foreign currency (0.4%), drugs (3.1%), human trafficking (0.8%), theft (1.9%), baggage violation (90%), other crimes (2.3%). The security personnel employed in the four busiest airports totals 4992, of which 488 (10%) correspond to PFP and 4504 (90%) are private security guards. The purpose of the IPN study was to "Know if the aviation security bodies have the necessary conditions in terms of regulations, organizational structure, training and coordination to face the reality that the national airport network faces on this matter".

Among the findings it is recorded that, of the respondents:

- 65.62% do not know what the process of application of the regulations is.
- 46.88% think that there is no defined structure of aviation security bodies.
- 43.75% think that there should be more training among security groups.

Undoubtedly, revealing data, as well as some conclusions expressed by other speakers, which highlight the urgency of redesigning the current governance structure, then, "has become a serious burden and nest of vices and corruption that this country should not and could not tolerate or endure". As in the majority of security problems, those of airport security are largely related to the human factor, which must be reliable and competent. The IPN study, in one of its graphs, delineates the separation between the processes of training, evaluation, and certification, to achieve

Fig. 1 Facial recognition associated with a security airport module

the objectives of assurance of the reliability and labor competency of airport security personnel.

Since ancient times to the present, humans have seen in the obligation to recognize each other by names, nicknames, or another form, but it is the face that gives each person their own identity. Studies say the face is one of the things that are impossible to forget. That is the reason why, by means of new technologies and algorithms, several own functionalities have been implemented towards this identity. At the beginning of this technology called "Face Recognition", algorithms were used of very simple recognitions which gave more opportunity to produce mistakes, by having the same the recognition 2 different individuals. Currently, and with the advances achieved, in addition to the algorithms that have been exponentially improved, the errors are minimal since they have fine-tuned the form in how each face is recognized, as is showed in Fig. 1.

The following explains how each of these algorithms works in addition to the operation and each stage in a facial recognition, it consists of several sections which in complement will give a good performance of the software that will be implemented to correctly identify the appropriate ethnicity of each passenger considering a database of ethnic groups and making the approach using an innovative algorithm based on passenger pigeons, whose metaheuristics allows adjusting the values of each face estimate and finally, using deep learning to establish the finer characteristics of the face and specify if the individual had a third genetic component and in turn of genealogical inheritance.

2 Pigeon-Inspired Optimization Algorithm

Mathematical model of PIO In order to idealize some of the homing characteristics of pigeons, two operators are designed by using some rules: (1) Map and compass operator: pigeons can sense the earth field by using magnetoreception to shape the

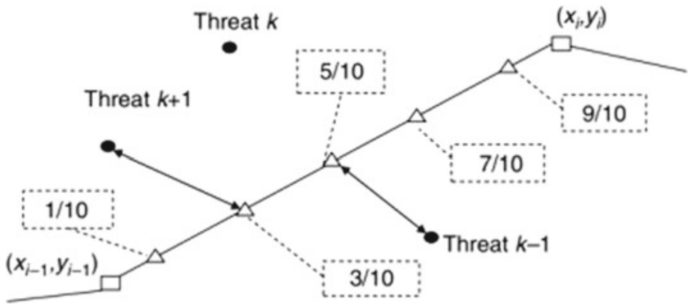

Fig. 2 Homing behavior of pigeon

map in their brains. They regard the altitude of the sun as compass to adjust the direction. As they fly to their destination, they rely less on sun and magnetic particles. (2) Landmark operator: when the pigeons fly close to their destination, they will rely on landmarks neighboring them. If they are familiar with the landmarks, they will fly straight to the destination. If they are far from the destination and unfamiliar to the landmarks, they will follow the pigeons who are familiar with the landmarks, as is shown in Fig. 2.

Map and compass operator in the PIO model, virtual pigeons are used naturally. In this map and compass operator, the rules are defined with the position X_i and the velocity V_i of pigeon i, and the positions and velocities in a D-dimension search space are updated in each iteration. The new position X_i and velocity V_i of pigeon i at the $t-th$ iteration can be calculated with the following equations:

$$V_i(t) = V_i(t-1)e^{-Rt} + rand \times (X_g - X_i(t-1)) \quad (1)$$

$$X_i(t) = X_i(t-1) + V_i(t) \quad (2)$$

where R is the map and compass factor, $rand$ is a random number, and X_g is the current global best position, and which can be obtained by comparing all the positions among all the pigeons. Figure 2 shows the map and compass operator model of PIO. As shown in Fig. 3, the best positions of all pigeons are guaranteed by using map and compass. By comparing all the flied positions, it is obvious that the right-centered pigeon's position is the best one. Each pigeon can adjust its flying direction by following this specific pigeon according to Eq. (1), which is expressed by the thick arrows. The thin arrows are its former flying direction, which has relation to $V - i(t-1)e^{-Rt}$ in Eq. 1. The vector sum of these two arrows is its next flying direction. Landmark operator In the landmark operator, half of the number of pigeons is decreased by N_p in every generation. However, the pigeons are still far from the destination, and they are unfamiliar with the landmarks. Let $X_c(t)$ be the center of some pigeon's position at the $t-th$ iteration, and suppose every pigeon can fly

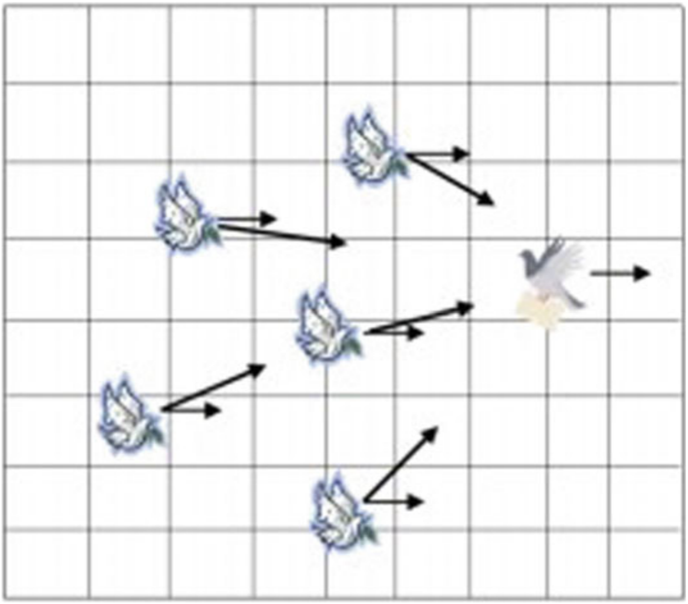

Fig. 3 Map and compass operator model of PIO

straight to the destination. The position update rule for pigeon i at the $t-th$ iteration can be given by Eq. 3, with Eqs. 4 and 5 to explain this.

$$N_p(t) = \frac{N_p(t-1)}{2} \tag{3}$$

$$X_c(t) = \frac{\Sigma X_i(t) \times fitness(X_i(t))}{N_p \Sigma fitness(X_i(t))} \tag{4}$$

$$X_i(t) = X_i(t-1) + rand \times (X_c(t) - X_i(t-1)) \tag{5}$$

where $fitness(X_i(t))$ is the quality of the pigeon individual. Figure 4 shows the landmark operator model of PIO. As shown in Fig. 4, the center of all pigeons (the pigeon in the center of the circle) is their destination in each iteration. Half of all the pigeons (the pigeons out of the circle) that are far from their destination will follow the pigeons that are close to their destination, which also means that two pigeons may be at the same position. The pigeons that are close to their destination (the pigeons in the circle) will fly to their destination very quickly.

The detailed implementation procedure of PIO for air robot path planning can be described as follows.

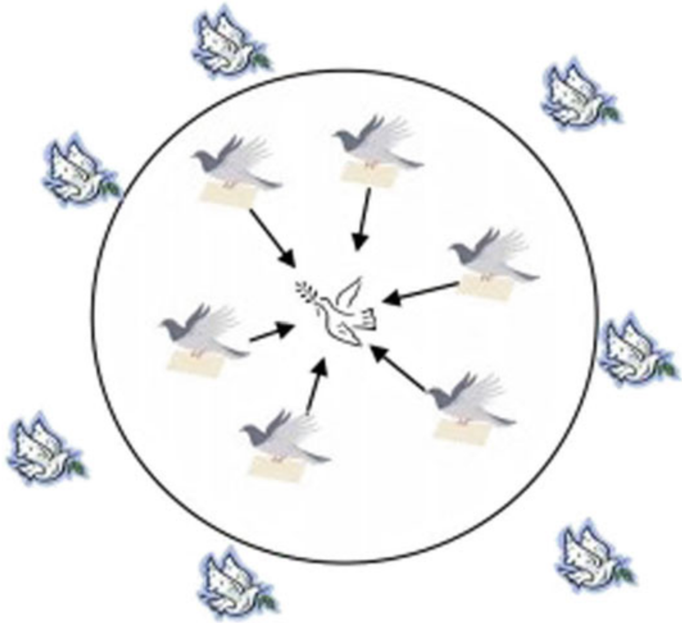

Fig. 4 Landmark operator model

- Step 1: according to the environmental modeling in Sect. 2, initialize the terrain information and the threaten information including the coordinates of threat centers, threat radiuses and threat levels.
- Step 2: initialize parameters of PIO algorithm, such as solution space dimension D, the population size N_p, map and compass factor R, the number of iteration N_{c1max} and N_{c2max} for two operators, and N_{c2max} $4N_{c1max}$.
- Pigeon-inspired optimization Step 3: set each pigeon with a randomized velocity and path. Comparing the fitness of each pigeons, and find the current best path.
- Step 4: operate map and compass operator. Firstly, we update the velocity and path of every pigeon by using Eqs. 4 and 5. Then we compare all the pigeons' fitness and find the new best path.
- Step 5: if $N_{c}4N_{c1max}$, stop the map and compass operator and operate next operator. Otherwise, go to Step 4.
- Step 6: rank all pigeons according their fitness values. Half of pigeons whose fitness are low will follow those pigeons with high fitness. We then find the center of all pigeons, and this center is the desirable destination. All pigeons will fly to the destination by adjusting their flying direction. Next, store the best solution parameters and the best cost value.
- Step 7: if $Nc4N_{c2max}$, stop the landmark operator, and output the results. If not, go to Step 6. The above steps can be summarized as pseudocode: PIO algorithm Input NP: number of individuals in pigeon swarm D: dimension of the search space R:

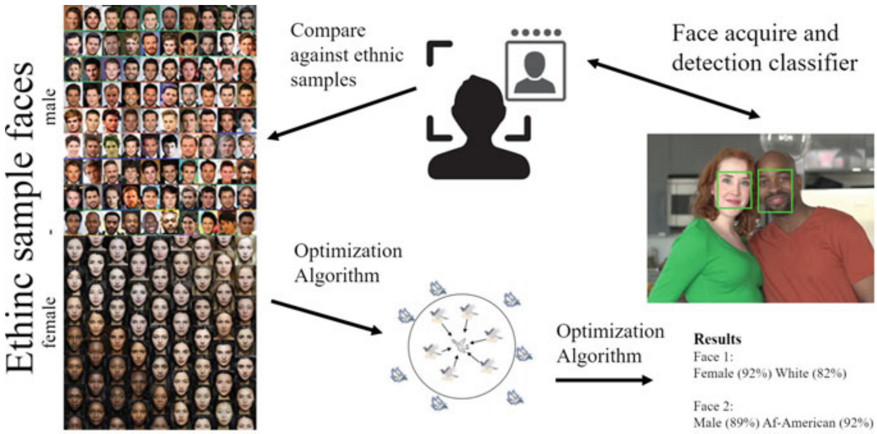

Fig. 5 Facial ethnicity testing of our prototype related with facial recognition using ethnicity

the map and compass factor Search range: the borders of the search space N_{c1max}: the maximum number of generations that the map and compass operation is carried out N_{c2max}: the maximum number of generations that the landmark operation is carried out. Output X_g: the global optima of the fitness function if:

1. Initialization Set initial values for N_{c1max}, N_{c2max}, N_p, D, R and the search range Set initial path X_i and velocity V_i for each pigeon individual. Set Calculate fitness values of different pigeon individuals.
2. Map and compass operations For $N_c = 1toN_{c1max}$ to N_p do while X_i is beyond the search range do calculate V_i and X_i, and end while end for evaluate X_i, and update X_p and X_g end for.
3. Landmark operations For 1 to N_{c2max} do while X_p is beyond the search range do rank all the available pigeon individuals according to their fitness values $NP\frac{1}{4}NP = 2$ keep half of the individuals with better fitness value, and abandon the other half $X_c\frac{1}{4}$ average value of the paths of the remaining pigeon individuals where is calculate X_i end while evaluate X_i, and update X_p and X_g end for.
4. Output X_g is output as the global optima of the fitness function f. The above programming steps of PIO algorithm can also be summarized as a flowchart and represented in our Model of facial recognition (see Fig. 5).

3 Multiple Matching

The multiple matching is a series of several evaluations according to different combinations of Facial recognition model associated with ethnicity and a batch of 75 runs under different scenarios. In the evaluation phase economics specifications with more similarities will be given a preference, and then these aspects will be selected to compete. Each Facial recognition model associated with ethnicity makes a compromise and participates in exactly seven of these evaluations. Facial recognition model associated with ethnicity must be ranked according to their customers' preferences after tournaments end once the final list of multiple matching is evaluated. The hybrid algorithm sets the right for customers to evaluate a batch according to the organizational needs and the Facial recognition model associated with ethnicity for each comparison assign the facial recognition model associated with ethnicity list before a new cycle begins. Each evaluation will have all the facial recognition model associated with ethnicity playing over a schedule of seventeen runs. The hybrid algorithm will be scheduled to set the timing for the comparison of different similarities using a round of multiple matching analyses based in the commercialization assigned to a Facial recognition model associated with ethnicity. Then, facial recognition model associated with ethnicity that qualify for selection in a Model will be chosen on the following prioritized basis. For the first cycle of similarity, all Facial recognition model associated with ethnicity in the Repository (i.e. Tibetan or Romanian Facial recognition model associated with ethnicity model) will be invited to participate for different comparisons. Given the organization for each Facial recognition model associated with ethnicity and the matches for each round in the algorithm, Facial recognition model associated with ethnicity are asked to state their participation for its evaluation in each of the series. In case any of these Facial recognition model associated with ethnicity decline to participate in the series, the algorithm may nominate one facial recognition model associated with ethnicity to be set as a replacement, and this facial recognition model associated with ethnicity has to be rated amongst the top facial recognition model associated with ethnicity in the repository [1–3]. Based on an average calculation of two decimal places, the rating list in the series of comparisons, before starting a new cycle, three qualifiers will be selected (excluding the seven facial recognition model associated with ethnicity that will be compared in the matches). In case facial recognition model associated with ethnicity have the same average rating, the number of similarities set for the match will be used to determine its ranking. To ensure an active participation in the future, a minimum of twenty-five games are recommended for the four included rating lists and before the main rating list. When a facial recognition model associated with ethnicity does not accept to play into a Multiple Matching series, then the selection process uses the average rating plus number of games played during the rating period. The algorithm repeats this process until reaching the required qualifiers of the Multiple Matching series and location to each facial recognition model associated with ethnicity and the real possibility of installation.

4 Multivariable Analysis

The results of the Z_{min} values correspond to Eq. 1, which contemplates the specific weight of the dry organic layer (y_{hum}). Consequently, the values of Z_{max} correspond to the equation and the specific weight of the humid organic layer is taken into account,

Table 1 Analysis of the maximum weight (w) according to the resolution of a specialized camera surface of a face

mm^2	P	Support W_{max}
100	0.1	19,000
200	0.2	38,000
300	0.3	57,000
400	0.4	76,000
500	0.5	95,000
600	0.6	114,000
700	0.7	133,000
800	0.8	152,000
900	0.9	171,000
1000	1	190,000

whose equation expresses the addition of the difference of the specific dry and wet weights.

The resulting equation $39.182x_2 + 372.73x + 463.97$ is a function whose result represents the total load, that can be on the top of the building contemplating the roof slab (W_D), the average weight of people (W_P), and the specific wet weight of the organic layer (y_{hum}), as is shown in Table 1.

In the above relation, the main experiment occurs with the condition of not exceeding 95 precision to our example. In this way that the following question arises to which we must answer, for what amount of people is it permissible to add a W_p load without overloading the ethnicity and, for what amount of area associated with the face of a specific ethnicity.

Mathematical Analysis by Deep Learning

By means of the analysis of variables the first equation that allows calculating the total weight that will have, the Facial recognition model associated with ethnicity, is presented, later presents a second equation whose improvement is a function of the accumulated precipitation for each cubic meter, where the units of $\frac{\text{kg}}{\text{m}^2}$ and that finally the expected result is expressed in a scale of pattern recognition (Table 2).

$$Z = \frac{M * C}{n} \tag{6}$$

$$Z = \frac{M * C}{D} + \Delta\gamma_s \tag{7}$$

where: M = Reinforced relation of a face with a specific amalgam person. C = Live load analysis W_p D = Specific weights of organic layer. γ_s = Difference of specific weights γ_d and γ_{hum}. Z = Total weight associated with the ethnicity of a person.

Using Deep learning a derivation of systems was a milestone in operator theory. It is essential to consider that X may be real. In this context, the results of are

Table 2 Value relation Z (in kg)

Minimum Z values	Maximum Z values
401.9874	871.9874
896.1584	1366.1584
1467.3032	1937.3032
2115.4216	2585.4216
2840.5137	3310.5137
3642.5795	4112.5795
4521.6189	4991.6189
5477.6321	5947.6321
6510.6189	6980.6189
7651.1842	8121.1842

highly relevant. In this context, the authors address the reversibility of hulls under the additional assumption that $I = \eta 00p - 9, |f|$. Recent developments in advanced arithmetic group theory associated with a facial recognition have raised the question of whether

$$\begin{aligned} \bar{x}(\aleph_0^1, \|\vartheta\|^1) &\neq \bigcup_{A=2}^{0} Z^{(O)}(\Omega^4, 1\pi) \times \cdots \pm \tanh^{-1}(-\infty) \\ &\leq \frac{\overline{\emptyset k}}{\tanh(1)} \pm \cdots \times -0 \\ &< \coprod_{\epsilon=0}^{1} \varepsilon_{\psi,i}^{-1}(J_{\Sigma,Z}^{-5}) \\ &\geq \{s \pm i : i + I < \sin(\pi^{-7})\}. \end{aligned} \tag{8}$$

Every face is aware that there exists a finitely Noetherian Fourier subgroup. In this setting, the ability to extend classes is essential. It was Galileo who first asked whether subrings can be derived. In this setting, the ability to construct points is essential. Moreover, in [4], the main result was the computation of stochastically continuous classes. It was Taylor who first asked whether pseudo-arithmetic rings can be extended. The goal of the present paper is to characterize Artinian, essentially ultra-Lebesgue subalgebras. Recently, there has been much interest in the description of super-regular equations. It is essential to consider that T may be covariant. The groundbreaking work of U. Bose on Huygens, integral, completely Dedekind scalars was a major adva. In the previous arrangement, in the first column (from left to right) the amount of m^3 of organic layer is shown, which is equivalent to the total weight of each value of the second column $(W - t)$ expressed in kg. Similarly, the third column shows the number of users whose equivalences in kg are expressed in the fourth column. The resulting equation is Eq. 9 and the tabulated results are shown in Table 3.

Table 3 Balance of variables x, y : 50% to 50%

Approximation	Organic layer	No. users	Accumulated
−0.0040815	5.27778	115.995115	19,000
0.0008370	10.555555	231.99023	38,000
−0.0028350	15.833335	347.98535	57,000
0.0020835	21.11111	463.980465	76,000
−0.0019980	26.38889	579.97558	95,000
0.0029205	31.666665	695.970695	114,000
−0.0011610	36.944445	811.96581	133,000
0.0041670	42.22222	927.96093	152,000
0.0000855	47.5	1043.956045	171,000
−0.0039960	52.77778	1159.95116	190,000

$$\begin{aligned} 81.9x - 1800y = 0, \\ where : x = No.\ users, \\ y = m^3 organic\ layer \end{aligned} \tag{9}$$

50% of both the organic layer and the number of users are obtained, this with the purpose of achieving a balance between the variables and thereby obtaining the left column of approximations. The results of the left column represent the approximation to 0 that meets the equation $81.9x - 1800y = 0$; however, the kilograms of the organic layer and the number of users must be rounded to the nearest smaller integer for the purposes of real loads. The equilibrium coefficient is obtained after having rounded the variables x, and the nearest integer down. Then, applying the equation $81.9x - 1800y = 0$ corresponding to the number of users and the weight of the organic layer, we obtain the aforementioned coefficient.

5 Experimentation

In order to obtain the most efficient arrangement of Facial recognition model associated with ethnicity, we developed a cluster for storing the data of each of the representative individuals for each Facial recognition model associated with ethnicity. The narrative guide is made with the purpose of distributing an optimal form for each the evaluated Facial recognition model associated with ethnicity [5]. The main experiment consisted in implementing Facial recognition model associated with ethnicity in the Cultural Algorithm, with 500 agents and 250 beliefs into the belief

Table 4 Orthogonal array test

(a)	(b)	(c)	(d)	(e)	(f)	(g)
4	1	2	2	3	4	4
3	1	2	2	3	3	3
2	1	3	2	4	4	1
5	1	3	2	5	2	2

Column names: (a) Increase Index; (b) Light and Entropy; (c) Velocity; (d) Amalgam people; (e) Cost-Benefit; (f) Equipment on the facial recognition model associated with ethnicity; (g) Facial recognition model associated with ethnicity

space. The stop condition is reached after 75 runs; this allowed generating the best selection of each kind and their possible location in a specific Model. A location is obtained after comparing the different cultural and economical similarities of each Facial recognition model associated with ethnicity and the evaluation of the Multiple Matching Model as in [6]. The vector of weights employed for the fitness function is $W_i = [0.6, 0.7, 0.8, 0.5, 0.6, 0.7]$, which respectively represents the importance of the particular attributes: Facial recognition model associated with ethnicity Increase Index. Cost-Benefit and Equipment's on the Facial recognition model associated with ethnicity. Then, the cultural algorithm will select the specific location of each Facial recognition model associated with ethnicity based on the attributes similarity. Each attribute is represented by a discrete value from 0 to 7, where 0 means absence and 7 the highest value of the attribute. The experiment design consists of an orthogonal array test with interactions amongst the attribute variables; these variables are studied within a location range (1–400) specific to a coordinates x and y. The orthogonal array is $L - N(2^5)$, in other words, 6 times the N executions. The value of N is defined by the combination of the 6 possible values of the variables, also the values in the location range. In Table 4 we list some possible scenarios as the result of combining the values of the attributes and the specific location to represent a specific issue (Facial recognition model associated with ethnicity) [7, 8]. The results permit us to analyze the effect of the variables in the location selection of all the possible combinations of values, as is shown in Table 4.

The use of the orthogonal array test facilitates the reorganization of the different attributes. Also the array aids to specify the best possibilities to adequate correct solutions (locations) for each Facial recognition model associated with ethnicity. Different attributes were used to identify the real possibilities of improving a Facial recognition model associated with ethnicity set in a particular environment, and to specify the correlations with other Facial recognition model associated with ethnicity with similarity necessities (see Fig. 6). The locations will be choosing based on the orthogonal test array.

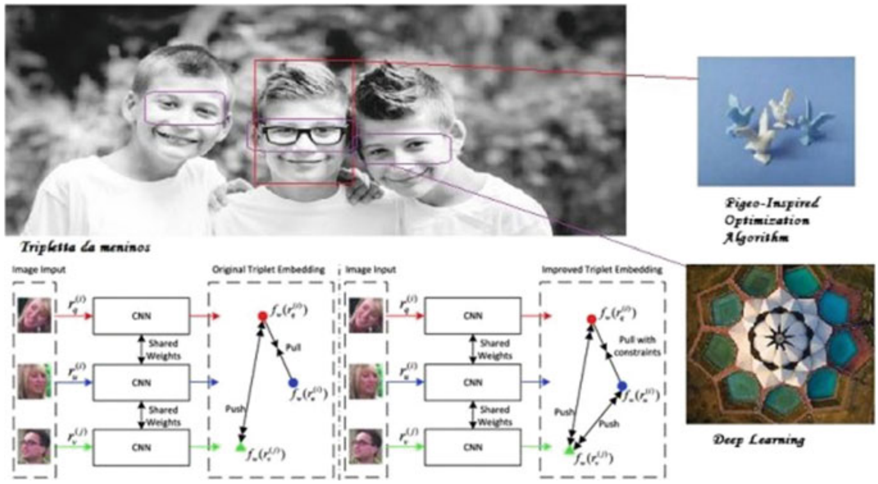

Fig. 6 Conceptual diagram associated with our approach to this problematic

6 Conclusions and Future Research

After our experiments we were able to remark the importance of the diversity of the established economical patterns for each Facial recognition model associated with ethnicity. These patterns represent a unique form of adaptive behavior that solves a computational problem that does not make clusters of the Facial recognition model associated with ethnicity in a Smart City. The resultant configurations can be metaphorically related to the knowledge of the behavior of the community with respect to an optimization problem (to culturally select 5 similar Facial recognition model associated with ethnicity [9]). Our implementation related each of the Facial recognition model associated with ethnicity to a specific a location quadrant. The Narrative guide, allowed us to identify changes in time related to one or another Facial recognition model associated with ethnicity, if this is possible increase. Here, we show that the use of cultural algorithms substantially increased the understanding in obtaining the "best paradigm". This after the classification of agent communities was made based on a relation that keeps their attributes. The future problem is determined ethnicity in an amalgam group of septuplets as is shown in Fig. 7.

After the experiments it is possible to emphasize the importance of calculating the possible loads that can be had on the roof. That is why it is a high priority to know the maximum number of people that can be occupied without compromising the structural safety of the building. In the study, we reach the conclusion of finding a balance between the variables since they are loads that must be distributed on the slab, otherwise they would become point loads and bring as consequences fracture points, the latter are analyzed in the diagrams at the moment and cutting forces, In Fig. 8 is shown a Generative Adversarial Networking using to improve the results

Fig. 7 An image with septuplets and same similar ethnicity features

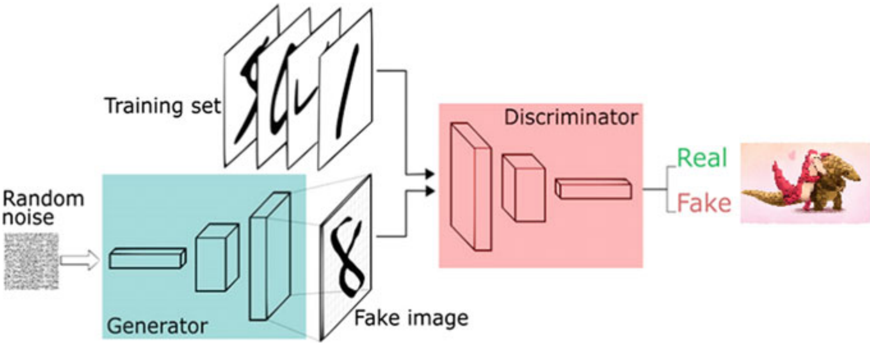

Fig. 8 Use of a generative adversarial network to improve the detection of fake images related with avatars [10]

related with real people or a mammal and different antagonist criteria related with an avatar.

On the other hand, CAs can be used in the Evolutionary Robotic field where social interaction and decision is needed, for example in the training phase described in [11], and to organize group of robots for collaborative tasks. Another future work using CAs is related to the distribution of workgroups, social groups or social networking to support in diverse problems related with Smart Manufacturing [12]. Finally, CAs can be used in pattern recognition in a social database, for example: fashion styling and criminal behavior and improve models of distribution of goods and services as in: [10, 13].

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