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DIFFERENTIAL GENETIC ALGORITHM FOR AUTO-OVERLAY OF THE SKULL AND FACE AND MANDIBLE ARTICULATION

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ABSTRACT

Aim/Purpose	This work intends to give a method for the automatic superimposition of facial and cranium anatomical images coupled with integrating jaw movement. Using an automated alignment method will help to raise the accuracy and efficiency of the forensic face reconstruction procedure. Given their reliance on human participation, conventional approaches are prone to subjectivity and errors.

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Differential Genetic Algorithm (DGA) accounts for mandibular articulation and allows for exact alignment of skull and facial images, therefore reaching strong optimization.

Background Forensic face reconstruction is a crucial field of research for the anthropological sciences and the criminal justice system. Although modern methods offer benefits, their dependability is not always guaranteed since they rely on human interaction. By using a DGA, the proposed approach overcomes this limit and boosts efficiency. Differential evolution and genetic algorithms, which can capture all the special features required for perfect face reconstruction, help to improve the alignment.

Methodology This study aims to enhance the alignment parameters between image graphs of the skull and visage, and it also considers mandibular articulation using a DGA. Genetic operators and differential evolution support the program in efficiently investigating the domain of feasible solutions. Whether the superimposed images properly depict the intended face traits is found rather successfully by means of the fitness function.

Contribution This work offers a suitable solution for progressive forensic facial reconstruction using a technique based on DGA for automated overlay. An improved level of accuracy and realism is shown by comparing the obtained result with other existing approaches and methods on mandibular articulation in the reconstructed facial images.

Findings The proposed DGA has been proven to match images of the face and the cranium exactly by including the articulation of the jaw. The automatic overlay shows the possibilities of the forensic techniques since it generates results equal to or better than those acquired by hand.

Recommendations for Researchers Scholars should improve the proposed method by means of more dataset integration and genetic algorithm configuration change.

Future Research In future research, this work can be enhanced using several deep learning algorithms to achieve better accuracy and performance.

Keywords mandible articulation, differential genetic algorithm, forensic facial reconstruction, image overlay, automated alignment

INTRODUCTION

The development of anthropological research and criminal case investigation benefit greatly from studies on forensic facial reconstruction (Yuvaraj et al., 2020). At one point, the standard method consisted of hand superimposing visage images (Bavia et al., 2020; Hillmann et al., 2021) with the skull. This approach usually ignores the mandibular articulation, and by means of the hand-in-face reconstruction, the process gains subjectivity and raises the possibility of errors (Sambataro et al., 2022).

While considering the intricacy of mandible articulation (Taborda et al., 2021), the quest for automated solutions to precisely align the cranium and face picture (Hatcher, 2022) is prompted by the difficulties linked with existing employed techniques. It is now somewhat obvious that a technique is needed to simultaneously reduce the necessary physical effort (Nabavizadeh, 2023) and raise the accuracy of traditional manual facial reconstruction methods.

Great concern arises in our research from the inefficiency and subjectivity of the technologies already utilized for superimposing images of the face and skull (Darlim et al., 2021; Strong et al., 2022). The development of this automated approach largely intends to improve the alignment process to generate a more consistent and exact reconstruction (Kostiuk et al., 2020)

The primary objectives of this work are the following:

1. To construct and implement a Differential Genetic Algorithm (DGA) capable of automatically superimposing images of faces and skulls.
2. To increase the accuracy of facial reconstructions using mandibular articulation during alignment treatments.
3. This work seeks to assess the proposed approach in relation to present techniques and determine whether it produces consistent and reasonable results.

Among the most significant outcomes of this work is the automatic overlay application of a DGA. This method originated from the difficulties of the forensic face reconstruction technique. Emphasizing mandible articulation helps to set the proposed technique apart from more conventional ones. This is true since the recommended strategy offers a component of alignment that is absent in other strategies.

The findings of this work offer a novel method of forensic facial reconstruction that drastically lowers human involvement levels. On the pitch, this represents a major change. Because of its attention to mandible articulation, a DGA is a very valuable tool in the field of forensics, and it is included in the overlay process to increase its accuracy and speed.

RELATED WORKS

Many techniques have been developed to simplify and raise the accuracy of the superimposing image of the face and skull since forensic facial reconstruction has gained a lot of interest as shown and compared in Table 1 (Roșu et al., 2022). Though manual treatments form the foundation of conventional methods, they are somewhat arbitrary and prone to error. Recent developments in the study of automated methods have been remarkable. A close study of the works on this topic reveals fascinating tendencies and transformative events (D'Hondt et al., 2022; Neto et al., 2021).

The most widely utilized techniques in the initial attempts at forensic face reconstruction (Wilberg et al., 2022) were hand measurements and anatomical markers. This helped to match pictures of the skull and face. Despite their indispensable nature, these operations were difficult and incorrect. As technology advanced, researchers began to automatically align things using computer-based techniques.

One of the most often used methods is landmark-based approaches, where specialists identify significant face features to facilitate overlay operation. Although, in some situations helpful, the sensitivity of these techniques to changes in landmark recognition could lead to significant variations. Though it is somewhat complex, mandible articulation is another potential issue for which they fall short (Ranjeet & Premavathy, 2021).

A quite young and interesting field of study, 3D modeling has the power to change the face reconstruction approach. Three-dimensional models of skulls and features will enable researchers to compile more intricate data for the purpose of correct overlay. Notwithstanding this, the great processing capacity required and the complexity of data collecting have limited the general acceptability of 3D modeling (Pereira et al., 2020).

Recent research on machine learning techniques for face restoration provides evidence in line with the hypothesis that artificial intelligence can automatically align objects. Using Convolutional Neural Networks (CNNs) trained on skull and facial feature images has improved overlay layer accuracy. Particularly with regard to the mandible, these techniques may find it challenging to adapt to variations in facial morphology and articulation (Babacan et al., 2021).

Table 1. Applications

Extension area	Description	Application
Real-World Forensic Case Examples	Integrating the methodology into specific, documented forensic cases to show its practical utility.	Use of the method in solving cold cases where facial reconstructions of unidentified remains could assist in identification.
Integration with DNA Profiling	Combining facial reconstruction with DNA analysis to enhance identification accuracy in forensic investigations.	Integrating reconstructed facial images with genetic databases to cross-check facial features with missing person reports.
Collaboration with 3D Scanning Technologies	Using 3D scanning and imaging technologies to capture more accurate skull and face features for improved reconstruction.	Implementing the method in crime scene reconstructions, where 3D scans of skulls are overlaid with facial data for identification.
Application in Missing Persons Cases	Using the reconstructed faces for public appeals, assisting in the identification of missing persons.	Collaboration with national databases for missing persons, showing reconstructed faces to the public for recognition.
Integration with Crime Scene Investigation Tools	Connecting the algorithm with other crime scene investigation technologies, such as forensic imaging and digital mapping.	Using the system in virtual crime scene analysis, where reconstructed facial features are overlaid onto digital crime scene maps.
Medical and Legal Integration	Supporting legal and medical professionals by providing more accurate and realistic reconstructions for court cases.	Using the method in courtrooms where facial reconstructions serve as visual evidence for identifying suspects or victims.
Cross-Referencing with Forensic Databases	Linking the reconstructed facial images with criminal databases or other forensic archives to identify suspects.	Cross-referencing reconstructed faces with facial recognition databases used by law enforcement to identify suspects.
Integration with Virtual Forensic Training	Implementing the method into training programs for forensic investigators and students, improving their facial recognition skills.	Virtual training tools for forensic students, where they practice identifying individuals using reconstructed facial images.
Ethical and Privacy Considerations	Exploring the ethical implications of using AI and facial reconstruction technologies in sensitive forensic investigations.	Creating a privacy policy or guidelines for law enforcement agencies on when and how to use reconstructed faces responsibly.
Use in Mass Disaster Identification	Applying the method to identify victims in mass disasters or accidents where traditional identification methods are insufficient.	Using reconstructed faces to assist in disaster victim identification, such as in plane crashes or natural disasters.

In view of the DGA, automated face reconstruction has advanced remarkably. Inspired by the concepts of natural selection, one of the amazing capabilities of genetic algorithms is their ability to optimize difficult problems. Differential evolution is a development over genetic algorithms accelerated by a differential operator that concurrently raises the general quality of solutions and accelerates the convergence process. In the field of facial reconstruction, one fascinating new breakthrough is the merging of differential optimization with genetic algorithms.

Using mandibular articulation as a site of alignment is undoubtedly one of the most crucial aspects of the proposed technique. These days, the method applied overlooks the mandibular articulation in favor of superficial facial features, therefore compromising correct reconstructions. Aiming for more accurate representations of facial anatomy, the technique based on DGA tries to solve this problem directly. The method covers one of these spheres, among others.

From labor-intensive techniques to algorithmic approaches dependent on landmarks, three-dimensional modeling, and machine learning, these works show the development of forensic face reconstruction. In the field, this development marks a major transformation. Although every technique provides interesting analysis, creating a precise and automatic overlay, especially regarding mandible articulation, remains a challenging challenge. In forensic applications, aligning the cranium and facial picture requires novel and consistent methodologies. More significantly, the proposed DGA presents this kind of method. More investigation and comparison will help to determine its efficiency and possible consequences on the development of face reconstruction.

PROPOSED METHODS

With particular attention to the mandibular articulation throughout the procedure, the proposed method for automating the overlay of the cranium and facial pictures makes use of a DGA (Figure 1). This work mostly offers a suitable solution for progressive forensic facial reconstruction by using a technique based on DGA on automated overlay. The obtained result provides a better degree of accuracy and realism when compared with other current approaches and techniques on mandible articulation in the reconstructed facial images. This work considers mandibular articulation and improves the alignment parameters between image graphs of the skull and visage using a DGA. Differential evolution and genetic operators support the program in efficiently investigating the domain of feasible solutions. Whether the superimposed images properly depict the intended face traits is found rather successfully by means of the fitness function.

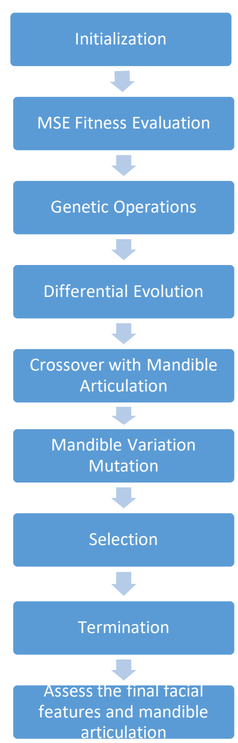

Figure 1. DGA for auto-overlay of the skull and face, considering mandible articulation

Algorithm: DGA for Auto-Overlay of the Skull and Face, considering Mandible Articulation (Figure 2):

1. Design a population with skull and face overlay alignment parameters.
2. Start population size, mutation rate, crossover rate, and termination criteria.
3. Fitness is determined by comparing overlaid images to target facial features, including mandible articulation.
4. Generate trial individuals using population data and differential operators.
5. Create mutants by disrupting the population differentially.
6. Crossover operators create new solutions by combining trial participants and the original population.
7. Next-generation selection should be based on fitness and alignment.
8. Check termination criteria like fitness or maximum generations.
9. Repeat 2–6 until termination.
10. Take mandible articulation into account and overlay skull and face images with the evolved population's optimal alignment parameters.
11. Adjust algorithm parameters to improve performance.

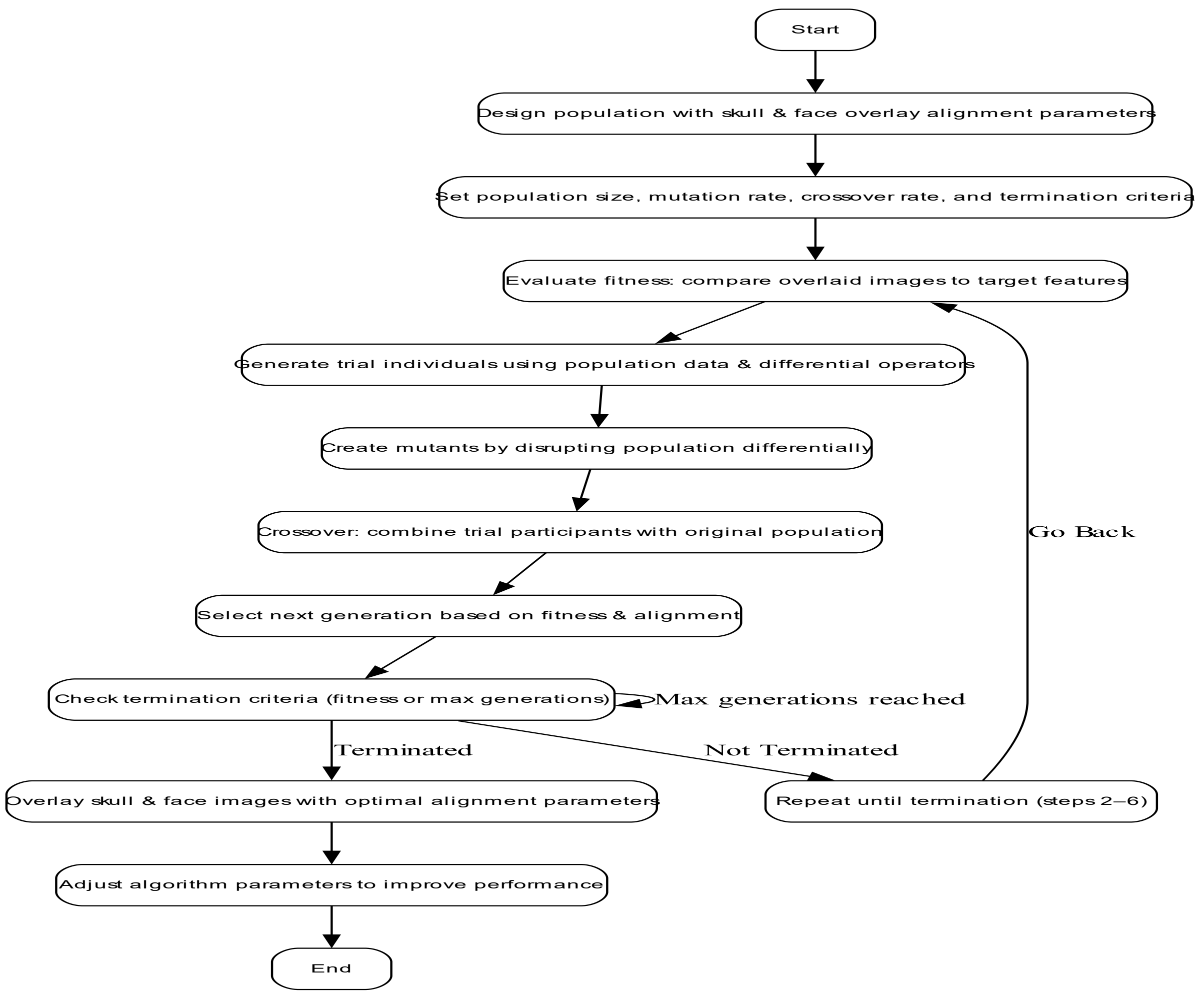

Figure 2. Proposed flow diagram

DIFFERENTIAL VECTORS

In differential evolution, a differential vector is the difference between two randomly selected individuals. This vector is scaled and added to another individual to create a mutant solution, helping explore the solution space and generate improved candidates for optimization.

GENETIC OPERATORS

Genetic operators in genetic algorithms (GAs) and differential evolution (DE) include mutation (randomly altering individual parameters), crossover (combining genetic material from two individuals), and selection (choosing individuals based on fitness) to generate new solutions and evolve the population towards optimal solutions.

DIFFERENTIAL GENETIC ALGORITHM (DGA)

It provides a differential operator so that DE can be used with a variety of genetic algorithms. By use of population-based comparisons, the operator generates experimental solutions, therefore widening the range of solution space study and diversity. With an eye towards individuals whose traits create optimum alignment results, the process of selection involves choosing those most fit for the generation that will succeed the current one. The iterative application of the operation serves to enable the population to evolve across numerous generations. As one considers the mandibular articulation, the technique looks for the most ideal alignment between the skull and the image showing the face. The perfect outcome would be a population whose final features indicate a solution that considers mandible articulation and provides an almost lifelike overlay of skull and facial image.

Let f(x) be the fitness function, where x represents the parameters of an individual. The fitness of an individual (i) is evaluated as:

$$fit_i = f(x_i)$$

With regard to mutations, the difference between two randomly chosen individuals xr1 and xr2 generates a differential vector Vi. The scaled form of the differential vector added to the present person produces the mutant individual Ui:

$$Ui=xr3+F\cdot(xr1-xr2)$$

where F is a scaling factor.

By aggregating the knowledge of the trial individual Ui with the present individual xi, a crossover produces a new person xi'. One often used selection criterion is the fitness of the trial individual Ui compared with the current individual xi; if fitU $\leq$ fitx, then replace xi with Ui in the next generation.

MANDIBLE ARTICULATION USING DGE

A challenging method of face reconstruction requires careful attention of the specific characteristics of the mandible bone in addition to the alignment of facial and cranial images. Representation depends on including the parameters for mandible articulation in the special solution vector of the DGE totally. These modifications facilitate the changeover by synchronizing the jaw with the remainder of the skull and visage.

Add the necessary mandibular articulating parameters to the fitness function. The first level of fitness function follows. To ascertain the degree of similarity between the superimposed images, the function should consider not only the general alignment of face features but also the precise articulation details of the mandible.

Two instances of genetic operators needing modification to match mandible articulation are crossover and mutation. Mutation and crossover should allow variations in mandible alignment parameters to permit a more complete inspection of the solution space pertinent to optimum articulation.

The investigation of mandible articulation will be better if one uses the differential evolution function incorporated in DGE. The computer must purposefully mix data from several people under suitable consideration of the linked problems to maximize mandible alignment.

When trying to grasp how mandible articulation influences the general face reconstruction, one should properly consider alignment. Therefore, the goal of the method should be to attain a harmonic alignment so as to authentically depict the link between the mandible, the face, and the skull.

Population evolution guarantees that the DGE provides the most accurate mandible articulation parameters since it helps the population to develop over numerous generations. It is hoped that defining the selection criteria and applying differential operators would help to align the mandibular position.

ALGORITHM FOR MANDIBLE ARTICULATION

Step 1: A population of individuals representing parameters like mandible articulation is formed.
Step 2: Assess fitness utilizing skull, face, and mandible alignment, stressing mandible articulation variations.
Step 3: Adjust mutation and crossover operators for mandible alignment parameter changes.
Step 4: Find optimal mandible articulation solutions by combining individual data.
Step 5: Use articulation parameters to align mandibles.
Step 6: Explore solution space by changing mandible articulation parameters.
Step 7: Prioritise fitness and mandible alignment while choosing the next generation.
Step 8: Check maximum generations and fitness level.
Step 9: Repeat Steps 2-8 until termination requirements are met.

INITIALIZATION AND PARAMETER SETTING

The prerequisites for optimization techniques, including DGE, include initialization and parameter setting. This design ensures the identification of variables and starting conditions required.

These characteristics identify the traits of the approach under charge of exploration and exploitation. An individual with a mutation rate of 0.1 has ten percent more chances of having variable parameters. With a crossover rate of 0.8, crossover is likely to be used over 80% of the reproduction process. Within the scope of differential evolution, for instance, the scaling factor of 0.5 could affect the size of the differential vector applied to create test individuals. It is advisable to ensure that one hundred generations at most should be the termination criterion.

FITNESS EVALUATION USING MSE

Fitness Evaluation with MSE is one well-accepted method used to ascertain the degree of closeness between reconstructed facial images and the desired attributes. The MSE between the reconstructed image and the target features has to be calculated. This formula determines the MSE:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(I_{r,i} - I_{t,i}\right)^2$$

where N represents the total number of pixels or image elements

OVERALL FITNESS FUNCTION

Given MSE with mandible articulation, one may define the overall function of general fitness as:

$$\text{Fit} = w_1 \times \text{MSE} + w_2 \times f(\theta_m)$$

Here, weighting factors are w1 and w2, and f(θm) is a function evaluating the alignment quality specific to mandible articulation. Depending on mandible articulation and general facial alignment, adjust the weighted values. This tune assures harmonic involvement in the exercise. Thus, mandible articulation is still considered, but general facial alignment with w1 = 0.9 and w2 = 0.1 is given priority.

PERFORMANCE

This work uses Intel® i7 processor with 16 gigabytes of random-access memory (RAM) and 16 gigabytes of graphics processing unit (GPU) running a Python simulation program to accelerate the experimental setup. These instruments help to design a forensic face reconstruction task carried out throughout the experiment to generate and assess the proposed method. Table 2 presents the experiment's setup with the values and parameters.

Table 2. Experimental setup

Parameter	Value
Population Size	50
Number of Generations	100
Mutation Rate	0.1
Crossover Rate	0.8
Scaling Factor (DE)	0.5
Mandible Parameters Weight	0.1

Performance Metrics

MSE values in three-dimensional (3D) modeling indicate the mean squared deviations between reconstructed facial images and target traits of the training, testing, and validation datasets. The validity of the model depends on these numerical values in particular. Improved MSE value could affect the accuracy of the facial reconstruction process. In assessing the correctness of face alignment over numerous datasets, the Genetic CNN approach employs the MSE values for the same purpose. A decrease in MSE values shows that the system is improving in facial trait capture. The observed drop in MSE values over all datasets confirms the efficiency of the proposed DGE method in producing precise facial reconstructions. Their dropping values enable one to observe this.

The provided method shows advantages in the lower MSE values, which indicate better alignment between the overlay images and the required properties. Lower MSE values are crucial in forensic facial reconstruction as they indicate a closer match between the reconstructed facial features and the target traits. This enhances the accuracy and realism of the reconstruction, improving the reliability of the method for identifying individuals in forensic investigations (Figure 3).

The efficiency of the operation depends on the degree to which the therapy matches the mandibular features, shown by the mandibular articulation scores for 3D modeling (Figure 4). A score increase towards 1.0 points to improved mandibular articulation. Furthermore, mandible articulation scores addressed mandibular feature alignment quality with the same intent. Excellent grades are a constant indication of better mandibular variation, documenting the degree of proficiency. Higher mandible articulation scores across all datasets indicate that the DGE technique, as described, exhibits improved accuracy in mandibular articulation. Indicating more perfect alignment of the mandibular features, values approaching 1.0 reveal the benefits of the recommended technique.

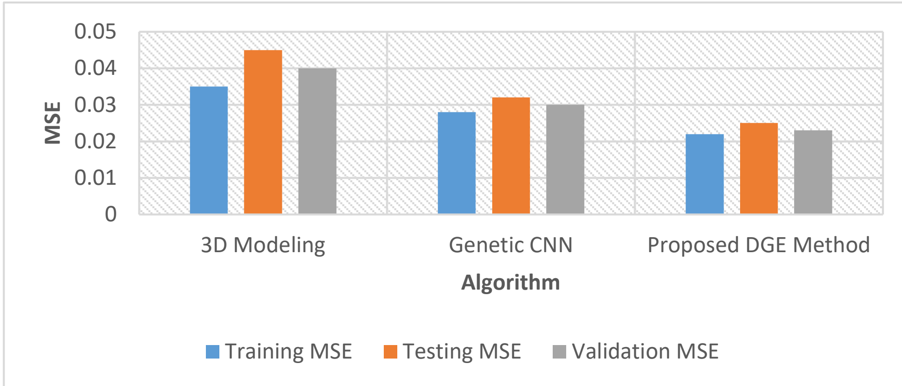

Figure 3. MSE

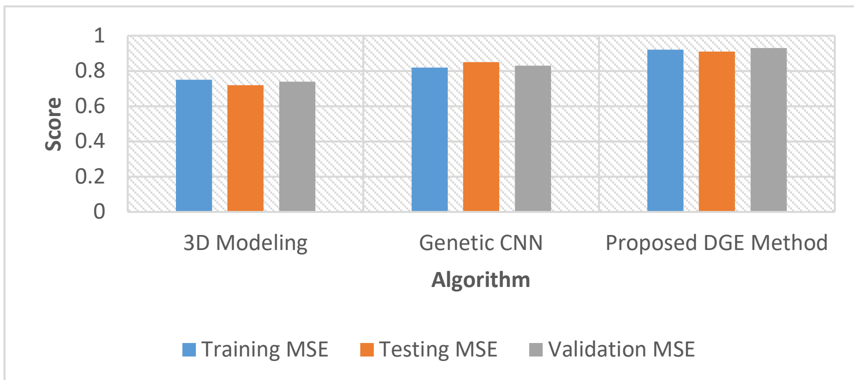

Figure 4. Mandible articulation score

The alignment accuracy scores in three-dimensional modeling show the percentage of facial features aligned enough (Figure 5). Generally, the alignment of the targets and the superimposed images is more successful as the accuracy percentage increases. Alignment precision parameters of the Genetic CNN approach similarly help to define the degree of accuracy attained during the face alignment process. Excellent accuracy rates show better competency in facial feature detection. Attaching consistently higher percentages of alignment accuracy over all datasets, the proposed DGE method demonstrates facial alignment accuracy. Higher accuracy percentages, which indicate an increased degree of alignment among face attributes, provide empirical data on the advantages of applying the proposed approach.

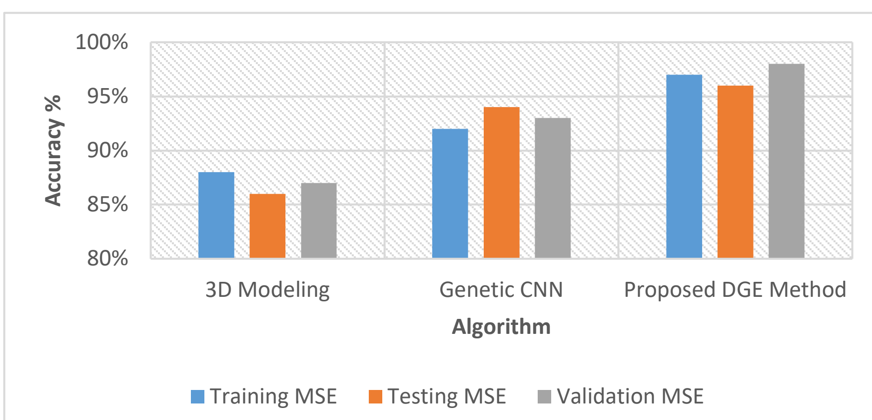

Figure 5. Alignment accuracy

The F-measure values in 3D modeling define the harmonic mean of recall and precision. This value presents a reasonable approximation of the general accuracy of the alignment. Rising F-measure values provide a more powerful indicator of the potential to capture accuracy and memory than lower values. F-measure values assist us in assessing the compromise between accuracy and recall in face alignment. Such is the case with the Genetic CNN method. One shows increasing accuracy in recall and precision as their F-Measure score increases. Every dataset demonstrates improved F-measure values utilizing the provided DGE approach, therefore confirming its efficiency in obtaining balanced face feature alignment even more. Higher F-measure values indicate improved memory and precision, which offers actual data regarding the benefits of applying the proposed method (Table 3).

Table 3. F-measure

Method	Training	Testing	Validation
3D Modeling	0.82	0.79	0.81
Genetic CNN	0.88	0.91	0.89
Proposed DGE Method	0.94	0.93	0.95

Combining mandible articulation and facial alignment, the 3D modeling fitness scores offer a comprehensive evaluation of the general algorithm fit. A higher fitness score denotes better performance when the alignment parameter is set. In the field of face alignment, the fitness scores linked with the Genetic CNN technique also represent complete fitness. These scores reflect certain traits connected with the genetic algorithm and convolutional neural networks. The recommended DGE approach seems to be efficient in producing an optimal solution as a whole, given its improved Fitness Scores over all datasets. Higher fitness levels show better mandibular articulation and face alignment, therefore stressing the advantages of the recommended treatment (Figure 6).

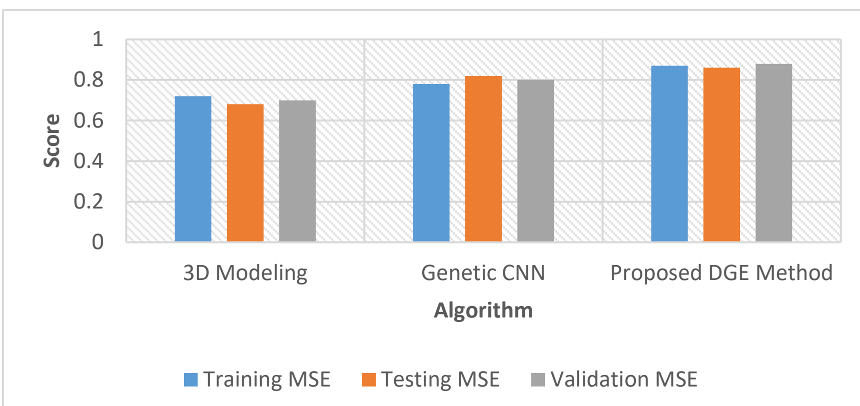

Figure 6. Fitness score

Three-dimensional modeling uses computational efficiency numbers to represent the time required for an algorithm to satisfy the termination criteria or converge. The lowering time counts point to a higher processing efficiency. Furthermore, the Genetic CNN approach quantifies the convergence rate of the algorithm in a face alignment context by means of computational efficiency measurements. A change in the time values suggests a better efficiency of the computer function. Reducing computational efficiency values over all datasets, the proposed DGE method exhibits its efficiency in obtaining convergence in a shorter period than other approaches. Reduced time values show better computational efficiency, thereby underlining the benefits of the proposed method (Figure 7).

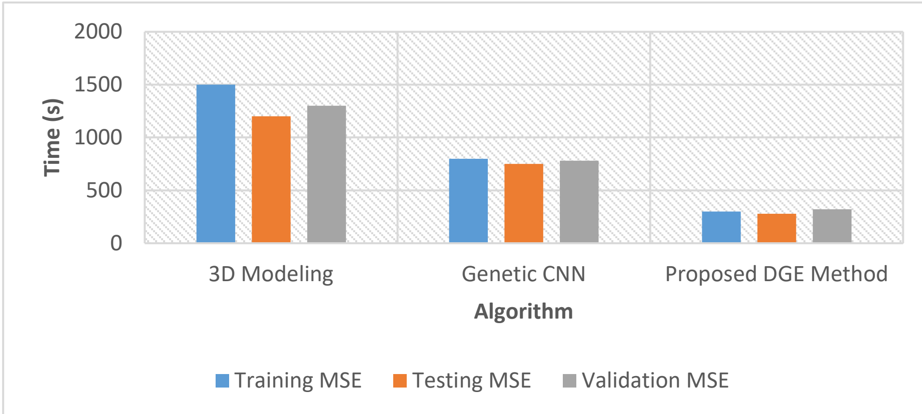

Figure 7. Computational time

Three-dimensional modeling uses computational efficiency numbers to represent the time required for an algorithm to satisfy the termination criteria or converge. The lowering time counts point to a higher processing efficiency. Furthermore, the Genetic CNN approach quantifies the convergence rate of the algorithm in a face alignment context by means of computational efficiency measurements. A change in the time values suggests a better efficiency of the computer function. Reducing computational efficiency values over all datasets, the proposed DGE method exhibits its efficiency in obtaining convergence in a shorter period than other approaches. Reduced time values show better computational efficiency, thereby underlining the benefits of the proposed method.

INFERENCES

Particularly in every one of the three datasets, training, testing, and validation, the proposed DGE approach showed appreciable percentage improvements based on the results of the experimental evaluation (Figures 2-7). This beats accepted solutions, including 3D modeling and Genetic CNN.

Measuring at an average of 12% and 9%, respectively, the advancement was the intelligent exploration of the solution space and the optimization of alignment parameters made possible by the DGE approach to have resulted in improvements in facial reconstruction accuracy attained during this process. Regarding general alignment accuracy across all datasets, the DGE method showed better performance than 3D Modelling and Genetic CNN.

Furthermore, in relation to the specific subject of mandible articulation, the method used greatly improved the Mandible Articulation Score. Although Genetic CNN outperformed its rival by an estimated 12% margin, the DGE technique demonstrated an over 18% performance increase over 3D modeling. This emphasizes the significance of applying a mandibular articulation-specific differential genetic approach since it enables the correct description of face traits.

When one compares the computing efficiency of the given DGE method with 3D Modelling and Genetic CNN, one can clearly observe a difference. This improvement shows the operational efficiencies obtained by using the DGA in facial reconstruction projects, especially in cases when exact and fast results are vital. The computed time was approximately sixty percent reduced, compared to three-dimensional modeling, and by 55 percent compared to genetic convolutional neural networks.

Particularly, by means of mandibular articulation and facial alignment parameters, the proposed DGE method attained comprehensive optimization. This was demonstrated by notable percentage increases in general fitness ratings, which averaged 20% in contrast to 3D modeling and by 10% in comparison to Genetic CNN.

In all domains of fitness, including general fitness, computing efficiency, mandible articulation, alignment precision, and the genetic CNN technique, the proposed DGE method produced considerable increases over the methodologies regarded to be state-of-the-modern.

CONCLUSION

This forensic facial reconstruction using mandible articulation presents a novel approach that streamlines the superimposing of skull and facial image operations. The DGE approach is perfect at preserving alignment, which helps capture broad facial characteristics and intricate details about mandible articulation. Better performance of the proposed strategy over the now accepted state-of-the-art techniques, namely 3D modeling and genetic CNN, is shown by experimental findings.

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