Recognizing surgically altered face Images using bat algorithm and comparison with genetic approach for trained and untrained images

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***Abstract* — Altering facial appearance using surgical procedures has raised a challenge for face recognition algorithms. Increasing popularity of plastic surgery and its effect on automatic face recognition has attracted attention from the research community. However, the nonlinear variations introduced by plastic surgery remain di cult to be modeled by existing face recognition systems. To overcome from these problems of existing system our proposed method uses BAT Algorithm which is a meta-heuristic optimization algorithm for premature and population diversity problem. On the plastic surgery face database, the proposed algorithm yields high identification accuracy as compared to existing algorithms and a commercial face recognition system.**

Keywords — recognizing surgically altered face; BAT algorithm;genetic algorithm

I. INTRODUCTION

A facial recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. One of the ways to do this is by comparing selected facial features from the image and a facial database. Facial recognition has received significant attention in the last few years Facial plastic surgery can be reconstructive to correct facial feature anomalies or cosmetic to improve the appearance Both corrective as well as cosmetic surgeries alter the original facial information to a great extent thereby posing a great challenge for face recognition algorithms.

In existing system, Multiobjective evolutionary algorithm is used to match face images before and after plastic surgery. Multiobjective evolutionary granular algorithm operates on several granules extracted from a face image. The first level of granularity processes the image with Gaussian and Laplacian operators to assimilate information from multi resolution image pyramids. The second level of granularity tessellates the image into horizontal and vertical face granules of varying size and information content. The third level of granularity extracts discriminating information from local facial regions. Genetic algorithm is used for feature selection and weight optimization for each face granule in the existing system. The evolutionary selection of feature extractor allows switching between two feature extractors and helps in encoding discriminatory information for each face granule.

The problem faced by using existing system is it fails to maintain diversity in a population which in terms decreases quality of solution. To overcome from these problems our proposed method uses BAT Algorithm which is a meta-heuristic optimisation algorithm for premature and population diversity problem. On the plastic surgery face database, the proposed algorithm yields high identication accuracy as compared to existing algorithms and a commercial face recognition system.

II. RELATED WORKS

The main aim in the paper Plastic Surgery: A New Dimension to Face Recognition, R. Singh, M. Vatsa, H. S. Bhatt, S. Bharadwaj, A. Noore, and S. S. Nooreyezdan,[] is to add a new dimension to face recognition by discussing this challenge and systematically evaluating the performance of existing face recognition algorithms on a database that contains face images before and after surgery.

The paper A Sparse Representation Approach to Face Matching across Plastic Surgery, G. Aggarwal, S. Biswas, P.J. Flynn, and K.W. Bowyer[1], introduce a novel approach customized to deal with the challenges of matching faces across variations caused by plastic surgeries. Both local and global surgeries may result in varying amount of change in relative positioning of facial features and texture. Though the overall face appearance changes, the resulting face typically resembles the original face in a part-wise manner. Unfortunately, these appearance variations are enough to cause most face matching approaches to show significant degradation in performance. Based on these observations, we propose to use a part-wise approach to deal with the challenges posed by these subtle variations in facial appearance.

In Component-based Face Recognition with 3D Morphable Models, B. Weyrauch, B. Heisele, J. Huang, and V. Blanz[2], a Support Vector Machine (SVM) based recognition sys- tem which decomposes the face into a set of components that are interconnected by a flexible geometrical model.The component-based system consistently outperformed global face recognition systems in which classification was based on the whole face pattern. A major drawback of the system was the need of a large number of training images taken from diffierent viewpoints and under diffierent lighting conditions.

In the work BBA: A Binary Bat Algorithm for Feature Selection, R. Y. Nakamura, L. Pereira, K. Costa, D. Rodrigues, J. P. Papa, and X.-S. Yang, [] the problem of the high dimensionality in object's description is addressed by means of finding the most informative features in a search space given by a Boolean hypercube. As the feature selection can be seen as an optimization problem, a bat-inspired algorithm is presented for this task. A binary version of the well-known continuous-valued Bat Algorithm was derived in order to position the bats in binary coordinates along the corners of the search space, which represents a string of bits that encodes whether a feature will be selected or not.

III. EXISTING SYSTEM

Face recognition algorithms either use facial information in a holistic way or extract features and process them in parts. In presence of variations such as pose, expression, illumination, and disguise, it is observed that local facial regions are more resilient and can therefore be used for efficient face recognition. They recognize faces using a combination of holistic approaches together with discrete levels of information. Feature extractors, namely Extended Uniform Circular Local Binary Pattern (EUCLBP) and Scale Invariant Feature Transform (SIFT) are used for extracting discriminating information from face granules. Every face granule has useful but diverse information which if combined together can provide discriminating information for face recognition. More-over psychological studies in face recognition shows that some facial regions are more discriminating than others and hence, contribute more towards the recognition accuracy. Feature selection methods are used for selective combination of features to assimilate diverse information for improved performance.

IV. PROPOSED SYSTEM

In proposed research when an individual undergoes plastic surgery facial features are reconstructed either globally or locally. In general this process changes the appearance investigate different aspects related to plastic surgery and face recognition. The pre-mature coverage and Population diversity problem can be overcome by applying BAT algorithm which efficiently selects features for optimization. Dimensionality reduction techniques offer solutions that both significantly improve the computation time and yield reasonably accurate clustering results in high dimensional data analysis.

V. IMPLEMENTATION

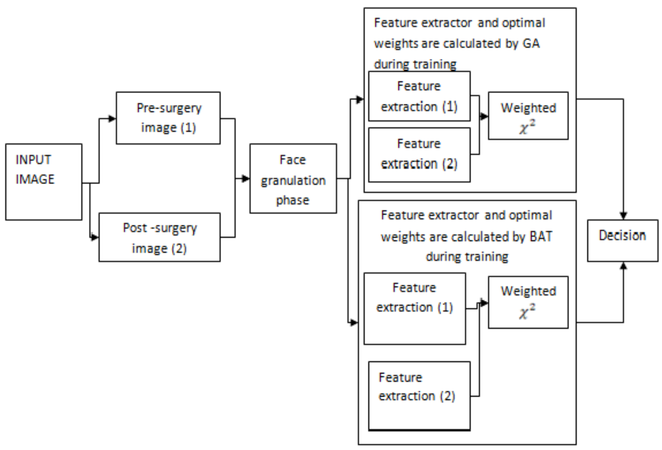

Fig. 1. Block diagram

System can be divided into 5 modules.

A. *Face Image Granulation*

Let F be the detected frontal face image of size n m. Face granules are generated pertaining to three levels of granularity. Thefirst level provides global information at multiple resolutions. This is analogous to a human mind processing holistic information for face recognition at varying resolutions. Inner and outer facial information are extracted at the second level. Local facial features play an important role in face recognition by human mind. At the third level features are extracted from the local facial regions.

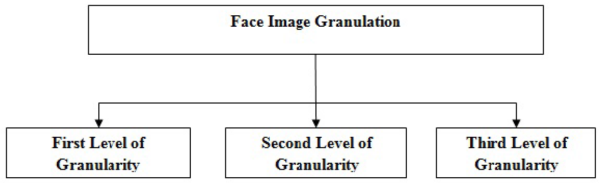

Fig. 2. Image Granulation

First Level of Granularity

In the first level, face granules are generated by applying the Gaussian and Laplacian operators. The Gaussian operator generates a sequence of low pass ltered images by iteratively convolving each of the constituent images with a 2D Gaussian kernel. The resolution and sample density of the image is reduced between successive iterations and therefore the Gaussian kernel operates on a reduced version of the original image in every iteration. Similarly, the Laplacian operator generates a series of band pass images. Let the granules generated by Gaussian and Laplacian operators be represented by FGri, where i represents the granule number.

Second Level of Granularity

The second level of granularity provides resilience to variations in inner and outer facial regions. It utilizes the relation between horizontal and vertical granules to address the variations in chin, forehead, ears, and cheeks caused due to plastic surgery procedures. To accommodate the observations of Campbell horizontal and vertical granules are generated by dividing the face image F into different regions.

Fig. 3. Horizontal Face Granules From The Second Level Of Granularity

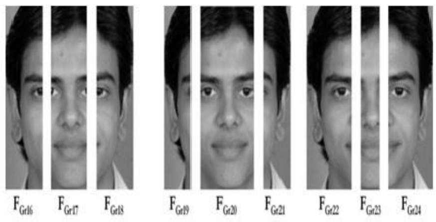

Fig. 4. Vertical Face Granules From The Second Level Of Granularity

In the above figures FGr7to FGr15 denote the horizontal granules FGr16to FGr24 denotes the vertical granules.

Third Level of Granularity

Human mind can distinguish and classify individuals with their local facial regions such as nose, eyes, and mouth. To incorporate this property, local facial fragments are extracted and utilized as granules in the third level of granularity. Given the eye coordinates, 16 local facial regions are extracted using the golden ratio face template.

B. Feature Extraction

In this research, any two (complementing) feature extractors can be used.

They are

a) Extended Uniform Circular Local Binary Patterns (EUCLBP) and

b) Scale Invariant Feature Transform (SIFT) are used.

Extended Uniform Circular Local Binary Patterns (EUCLBP) Extended Uniform Circular Local Binary Pattern (EUCLBP) is a texture based descriptor that encodes exact gray-level differences along with difference of sign between neighboring pixels. For computing EUCLBP descriptor the image is first tessellated into non-overlapping uniform local patches of size 32 by 32. For each local patch, the EUCLBP descriptor is computed based on the 8 neighboring pixels uniformly sampled on a circle (radius=2) centered at the current pixel. The concatenation of descriptors from each local patch constitutes the image signature. Two EUCLBP descriptors are matched using the weighted X2 distance.

Scale Invariant Feature Transform (SIFT) SIFT is a scale and rotation invariant descriptor that generates a compact representation of an image based on the magnitude, orientation, and spatial vicinity of image gradients. SIFT, is a sparse descriptor that is computed around the detected interest points. However, SIFT can also be used in a dense manner where the descriptor is computed around interest points. In this research, SIFT descriptor is computed in a dense manner over a set of uniformly distributed non-overlapping local regions of size 3232. SIFT descriptors computed at the sampled regions are then concatenated to form the image signature. Similar to EUCLBP, weighted 2 distance is used to compare two SIFT descriptors.

C. Multi-objective Evolutionary Approach for Selection of Feature Extractor and Weight Optimization

Feature selection problem embroils around two objectives: 1) select an optimal feature extractor for each granule, and 2) assign proper weight for each face granule. The problem of finding optimal feature extractor and weight for each granule involves searching very large space and finding several suboptimal solutions. Genetic algorithms (GA) are well proven in searching very large spaces to quickly converge to the near optimal solution Therefore, a multiobjective genetic algorithm is proposed to incorporate feature selection and weight optimization for each face granule.

Genetic Encoding: A chromosome is a string whose length is equal to the number of face granules i.e. 40 in our case. For simultaneous optimization of two functions, two types of chromosomes are encoded: (i) for selecting feature extractor (referred to as chromosome type1) and (ii) for assigning weights to each face granule (referred to as chromosome type2). Each gene (unit) in chromosome type1 is a binary bit 0 or 1 where 0 represents the SIFT feature extractor and 1 represents the EUCLBP feature extractor. Genes in chromosome type2 have real valued numbers associated with corresponding weights of the 40 face granules.

Initial Population: Two generations with 100 chromosomes are populated. One generation has all type1 chromosomes while the other generation has all type2 chromosomes.

- For selecting feature extractors (type1 chromosome), half of the initial generation (i.e. 50 chromosomes) is with all the genes (units) as 1, which represents EUCLBP as the feature extractor for all 40 face granules. The remaining 50 chromosomes in the initial generation have all genes as 0 representing SIFT as the feature extractor for all 40 face granules.
- For assigning weights to face granules (type2 chromosome), a chromosome with weights proportional to the identification accuracy of individual face granules is used as the seed chromosome. The remaining 99 chromosomes are generated by randomly changing one or more genes in the seed chromosome.

Further, the weights are normalized such that the sum of all the weights in a chromosome is 1.

Fitness Function: Both type1 and type2 chromosomes are combined and evaluated simultaneously. Recognition is performed using the feature extractor selected by chromosome type1 and weight encoded by chromosome type2 for each face granule. Identification accuracy, used as the fitness function, is computed on the training set and 10 best performing chromosomes are selected as parents to populate the next generation.

Crossover: A set of uniform crossover operations is performed on parents to populate a new generation of 100 chromosomes. Crossover operation is same for both type1 and type2 chromosomes.

Mutation: After crossover, mutation is performed for type2 chromosomes by changing one or more weights by a factor of its standard deviation in the previous generation. For type1 chromosome, mutation is performed by randomly inverting the genes in the chromosome.

The search process is repeated till convergence and terminated when the identification performance of the chromosomes in new generation do not improve compared to the performance of chromosomes in previous five generations. At this point, the feature extractor and optimal weights for each face granule (i.e. chromosomes giving best recognition accuracy on the training data) are obtained. Genetic optimization also enables discarding redundant and non-discriminating face granules that do not contribute much towards the recognition accuracy (i.e. the weight for that face granule is close to zero). This optimization process leads to both dimensionality reduction and better computational efficiency.

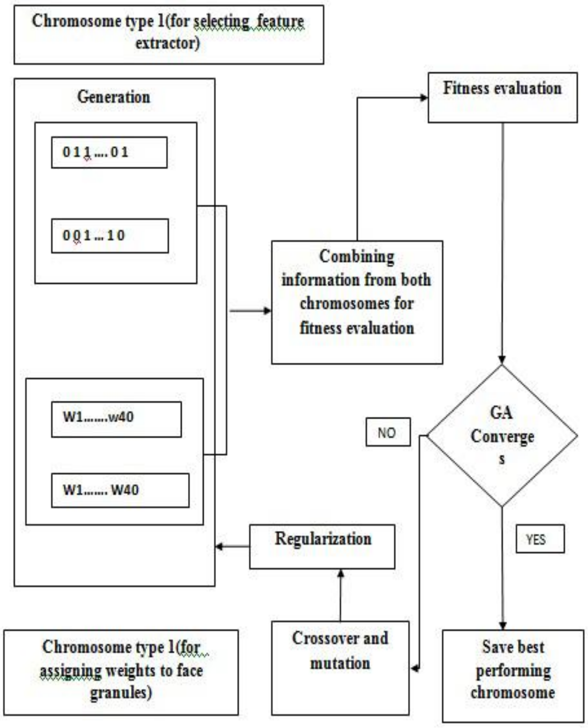

Fig. 5. Genetic Algorithm

D. *Multi-objective Evolutionary Approach for Feature Selection using BAT Algorithm*

In order to improve the variability of the possible solutions, Yang has proposed to employ random walks. Primarily, one solution is selected among the current best solutions, and then the random walk is applied in order to generate a new solution for each bat that accepts the condition in Algorithm:

xnew = xold + EA-(t)

in which A(t) stands for the average loudness of all the bats at time t and E between interval -1 and 1 attempts to the direction and strength of the random walk. For each iteration of the algorithm, the loudness Ai and the emission pulse rate ri are updated, as follows:

Ai(t + 1) = @Ai(t)

ri(t + 1) = ri(0)[1 - exp(-t)]

where @and are ad-hoc constants. At the first step of the algorithm, the emission rate (0) and the loudness (0) are often randomly chosen. Generally, (0) between interval 1 and 2 and (0) between interaval 0 and 1.

E. *Combining Face Granules with Multi-objective Evolutionary Learning for Recognition*

The granular approach for matching faces altered due to plastic surgery is summarized below.

- For a given gallery-probe pair, 40 face granules are extracted from each image.
- EUCLBP or SIFT features are computed for each face granule according to the evolutionary model learned using the training data.
- The descriptors extracted from gallery and probe images are matched using weighted X2 distance measure where a and b are the descriptors computed from face granules pertaining to a gallery-probe pair, i and j correspond to the ith bin of the jth face granule and j is the weight of the jth face granule. Here, the weights of each face granule are learnt using the Firefly algorithm.
- In identication mode (1: N), this procedure is repeated for all the gallery-probe pairs and top matches are obtained based on the match scores.

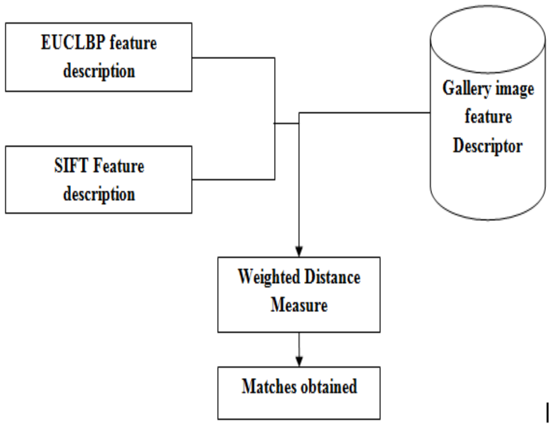

Fig. 6. Weight Optimization

VI. EXPERIMENTAL RESULT

The system is implemented using Matlab programming language. For this purpose Matlab 12 b is installed.

Plastic Surgery Face Dataset: One of the major challenges in this research is to prepare a database that contains images of individuals before and after facial plastic surgery. There are several concerns in collecting the database as patients are hesitant in sharing their images. Apart from the issues related to privacy, many who have undergone a disease correcting facial surgery would like to be discrete. To the best of our knowledge, there is no publically available facial plastic surgery database that can be used to evaluate current face recognition algorithms or develop a new algorithm. However, to conduct a scientific experimental study and to analyze the effect of both local and global plastic surgery on face recognition, it is imperative to collect face images before and after plastic surgery.

Dataset Description: The plastic surgery face database is a real world database that contains 1800 pre and post surgery images pertaining to 900 subjects. For each individual, there are two frontal face images with proper illumination and neutral expression: the first is taken before surgery and the second is taken after surgery. The database contains 519 image pairs corresponding to local surgeries and 381 cases of global surgery (e.g., skin peeling and face lift). For each individual, there are two frontal face images with proper illumination and neutral expression: the first is taken before surgery and the second is taken after surgery. The database contains 519 image pairs corresponding to local surgeries and 381 cases of global surgery (e.g., skin peeling and face lift). The following graph shows the Accuracy comparison for Genetic algorithm and BAT algorithm.

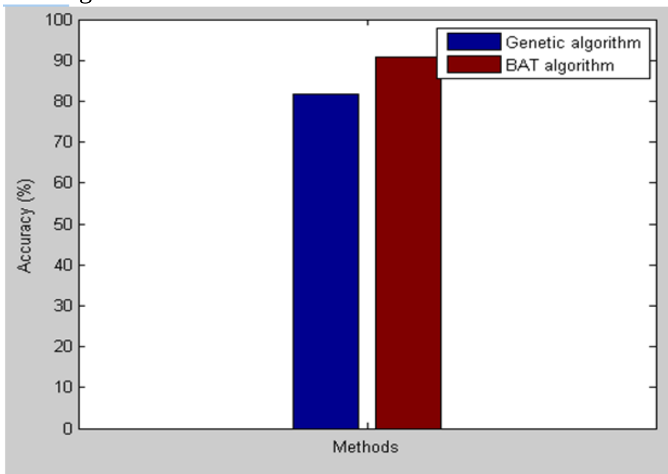

Fig. 7. Accuracy comparison graph(a)

In this accuracy is measured in percentage at Y-axis and methods are depicted in the X-axis. The accuracy values of the BAT algorithm for facial feature optimization are higher than the Genetic algorithm. Finally the proposed algorithm of the BAT algorithm achieves a higher level of the Accuracy value rather than the other algorithm.

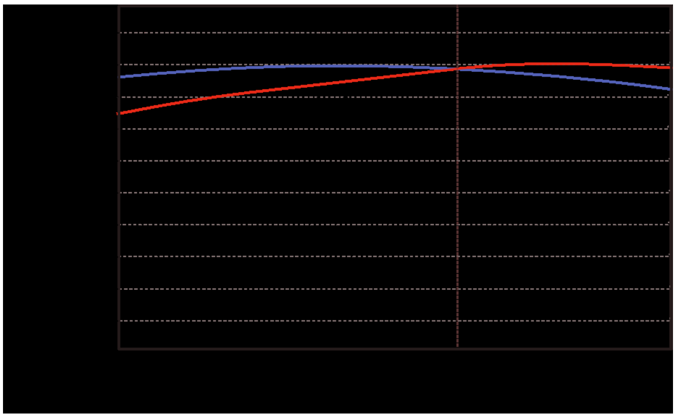

Fig. 8. Accuracy comparison graph(b)

In this graph, number of images is depicted in X axis and the accuracy is measured in percentage at Y-axis. The accuracy values of BAT algorithm are higher than genetic algorithm for trained images. In case of untrained images accuracy values of genetic algorithm has higher values.

VII. CONCLUSION AND FUTURE WORK

Plastic surgery has emerged as a new covariate of face recognition and its allure has made it indispensable for face recognition algorithms to be robust in matching surgically altered face images. This research presents a BAT approach that operates on several granules extracted from a face image.BAT algorithm is very simple and very flexible when compared to other swarm based algorithms as BAT does not require external parameters such as cross over rate and mutation rate etc., as in case of genetic algorithms, differential evolution and other evolutionary algorithms. Experimental results provides better result in terms of speed when compared with existing work .However the major challenge faced is the variations in the threshold values to be given when the number of images in the database changes. Based on the results, we believe that more research is required in order to design an optimal face recognition algorithm that can also account for the challenges due to plastic surgery. It is our assertion that the results of this work would inspire further research in this important area.

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