

## RECOGNIZING PRE AND POST SURGERY FACES USING MULTIOBJECTIVE EVOLUTIONARY FIREFLY ALGORITHM

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### ABSTRACT

In imaging discipline, image dispensation is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. The uses of techniques for escaping identification procedures are becoming popular because of massive acceptability and faster improvement of modern techniques. One such technique is varying facial appearance using surgical procedures that has raised a challenge for face recognition algorithms.

Plastic surgery procedures provide a proficient and enduring way to enhance the facial appearance by correcting feature anomalies and treating facial skin to get a younger look. Apart from cosmetic reasons, plastic surgery procedures are benefit for patients suffering from several kinds of disorders caused due to excessive structural growth of facial features or skin tissues. The security and privacy problem has been overcome. There is a possibility of attacking others privacy by Criminals or attackers using plastic surgery technology. Our proposed method deals better for overcoming such problems. Transmuting facial geometry and texture increases the intra-class variability between the pre- and post-surgery images of the same individual. Therefore, matching post-surgery images with pre-surgery images becomes an arduous task for automatic face recognition algorithms. Variations in pose, expression, illumination, aging and disguise are considered as

major challenges in face recognition and several techniques have been proposed to address these challenges. In Existing, multi-objective evolutionary granular algorithm is used to match face images before and after plastic surgery. 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 Firefly 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:** Extended Uniform Circular Local Binary Pattern(EUCLBP), Scale Invariant Feature Transform(SIFT), commercial-off-the-shelf (COTS), Sequential feature selection (SFS) and sequential floating forward selection (SFFS), Multi-Objective Firefly Algorithm (MOFA)

### 1. 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 and is increasingly being used for both identification (1: n) and verification (1:1) on large identity projects across the public and private sector. Facial recognition analyses characteristics of a person's face image input through a camera and can be broadly classified into static and dynamic/video matching. Facial recognition systems at a very high level work by

recognising a human face from scene and extract it. The system then measures nodal points on the face, distance between eyes, shape of the cheekbones and other distinguishable features. These nodal points are then compared to the nodal points computed from a database of pictures in order to find a match.

Plastic surgery procedures provide an easy way to enhance the facial appearance by correcting feature anomalies and treating facial skin to get a younger look. Apart from cosmetic reasons, plastic surgery procedures are beneficial for patients suffering from several kinds of disorders caused due to excessive structural growth of facial features or skin tissues. Plastic surgery procedures amend the facial features and skin texture thereby providing a makeover in the appearance of face. With reduction in cost and time required for these procedures, the popularity of plastic surgery is increasing. Even the widespread acceptability in the society encourages individuals to undergo plastic surgery for cosmetic reasons. According to the statistics provided by the American Society for Aesthetic Plastic Surgery for year 2012, there is about 9% increase in the total number of cosmetic surgery procedures, with over 500, 000 surgical procedures performed on face.

Different problems in face image analysis, such as face detection, face recognition and facial expression recognition have received very much attention in computer vision research. These problems are interesting from the viewpoints of basic research aiming to efficient descriptors for facial images and of applications such as surveillance and human-computer interaction .A key issue in face analysis are finding efficient descriptors for face appearance. Given the low inter person variation in face images; ideal descriptors should be very discriminative. Still, they should be robust to different perturbations and changes such as illumination and pose changes, aging of the subjects, etc. Despite the extensive research efforts towards face .descriptors robust to the aforementioned disturbances, the problems caused by blur often

present in the real world face images have been mostly overlooked. Blur may be present in face images due to motion of the subject or the camera during the exposure, camera not being in focus, or low quality of the imaging device such as analog web camera.

Image segmentation is a critical and essential component of image analysis system. It is one of the most difficult tasks in image processing because it determines the quality of the final result of analysis. Segmentation is basically clustering of the pixels in the image according to some criteria

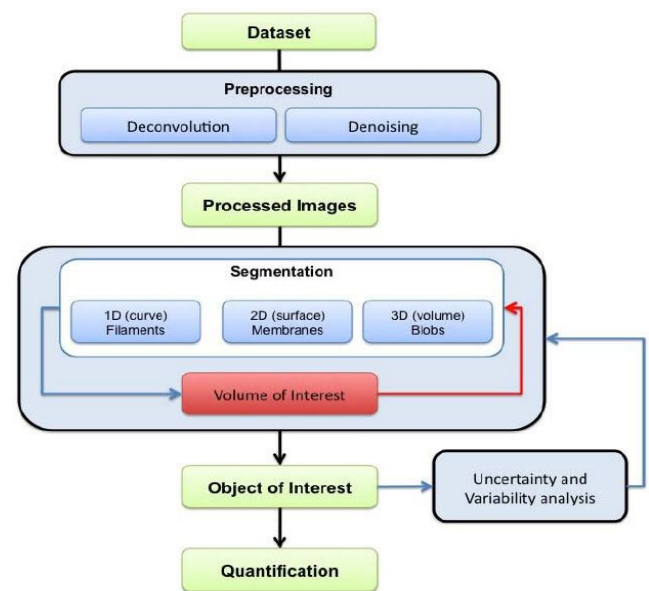


Figure 1: Image segmentation

### 3-dimensional recognition

A newly emerging trend, claimed to achieve improved accuracies, is . This technique uses 3D sensors to capture information about the shape of a face. This information is then used to identify distinctive features on the surface of a face, such as the contour of the eye sockets, nose, and chin.

One advantage of 3D facial recognition is that it is not affected by changes in lighting like other techniques. It can also identify a face from a range of viewing angles, including a profile view. Three-dimensional data points from a face vastly improve the precision of facial recognition. 3D

research is enhanced by the development of sophisticated sensors that do a better job of capturing 3D face imagery. The sensors work by projecting structured light onto the face. Up to a dozen or more of these image sensors can be placed on the same CMOS chip—each sensor captures a different part of the spectrum.

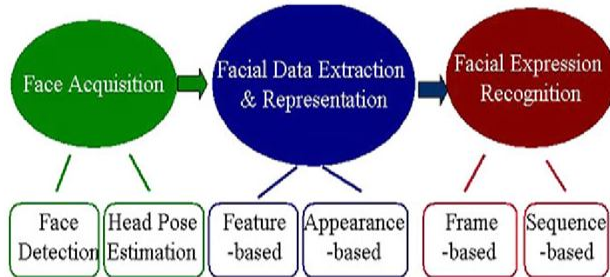


Figure 2: Face recognition and extraction techniques

### Introduction of the research

Current research presents a multi-objective evolutionary granular computing based algorithm for recognizing faces altered due to plastic surgery procedures. Proposed algorithm starts with generating non-disjoint face granules where each granule represents different information at varying size and resolution. Further, two 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. Finally, different responses are unified in an evolutionary manner using a multi-objective genetic approach for improved performance. The performance of the proposed algorithm is compared with a commercial-off-the-shelf face recognition system (COTS) for matching surgically altered face images against large scale gallery.

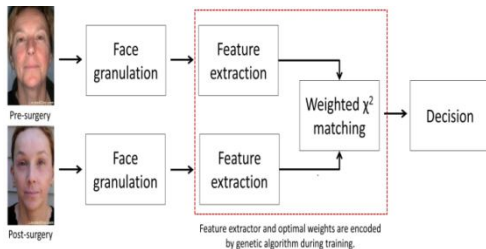


Figure 3: example of the face in research

## 2.PROBLEM DESCRIPTION

Face recognition is a well studied problem in which several approaches have been proposed to address the challenges of illumination, pose expression, aging and disguise, the growing popularity of plastic surgery introduces new challenges in designing future face recognition systems. Since these procedures modify both the shape and texture of facial features to varying degrees, it is difficult to find the correlation between pre and post surgery facial geometry. To the best of our knowledge, there is no study that demonstrates any scientific experiment for recognizing faces that have undergone local or global plastic surgery. The major reasons for the problem not being studied are:

Due to the sensitive nature of the process and the privacy issues involved, it is extremely difficult to prepare a face database that contains images before and after surgery. After surgery, the geometric relationship between facial features changes and there is no technique to detect and measure such type of alterations. Multi-objective evolutionary granular algorithm is used to match face images before and after plastic surgery. The problem faced by using this approach is it fails to maintain diversity in a population which in terms decreases quality of solution.

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. Moreover 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. Sequential feature selection (SFS) and sequential floating forward selection (SFFS) are widely used feature selection methods that evaluate the growing feature set by sequentially adding (or removing) features one-at-a-time. On the other hand, a definitive feature selection approach concatenates different features (for example, EUCLBP and SIFT) and performs dimensionality reduction using PCA to yield the final feature set.

### DISADVANTAGES

- It is not sufficient for improving the performance with single gallery evaluations.
- Offspring's that are exactly similar to parents.
- Crossover is not performed.
- Offspring's are generated randomly.

### 3. PROPOSED METHODOLOGY

Plastic surgery is used to repair and rebuild damaged skin and tissue. The damage may be the result of an inborn disease (a disease that is present from birth) or illness that develops later in life or an injury. The main aim of plastic surgery is to re-establish the functioning of skin and tissue to a level that is as close to normal as possible. Improving the appearance of the skin is an important secondary objective of plastic surgery.

Plastic surgery is used to

1. Adjust defects that are present from birth.
2. Restore skin and tissue damage resulting from disease or illness

3. Restore skin and tissue damage resulting from injury

Within these three broad groups, there are many different situations where plastic surgery may be needed, and a variety of different surgical procedures that can be used.

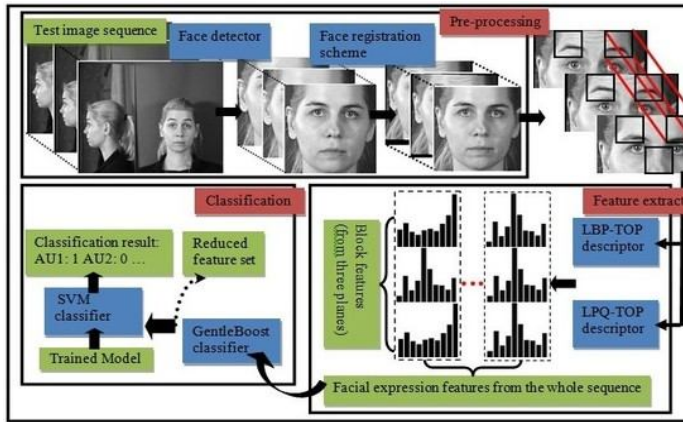
### Feature Extraction Based Genetic Approach for Face Recognition

Face Recognition algorithms either uses algorithms of two kinds, the algorithm which deals with the holistic image and the other type is the algorithm which extract features and process them as parts. Both the inner and outer facial regions in face recognition are used in producing diverse information. The observations states that surgical procedure if done, leads to change in more than one facial region. With large variations caused in the appearance, texture and shape of different facial regions, it has been a great challenge for the face recognition algorithms to match gallery image with the probe image. Certain issues have to be considered when performing face identification. They are,

- ❖ Size
- ❖ Position
- ❖ Orientation
- ❖ Illumination

Face detectors must have the capability to determine face images of different sizes, positions by scaling the image and by sliding a window over the image to adjust the position of the image. Depending on the direction of the light as well as the color it is one of the greatest challenges for the face recognition system to detect face images, which is otherwise called as the problem of illumination. Face recognition of matching pre as well as post-surgery images can be implemented with the help of different modules. They are,

- ❖ Face Granulation
- ❖ Feature Extraction
- ❖ Genetic Approach



**Figure 4: Face Feature Extraction using Proposed Algorithm**

**Implementation Phases**

- Face image granulation
- Feature extraction
- Multi-objective Evolutionary Approach for Selection of Feature Extractor and Weight Optimization
- Combining Face Granules with Multi-objective Evolutionary Learning for Recognition.

**Phase 1: Face image granulation**

Let  $F$  be the detected frontal face image of size  $n \times m$ . Detected frontal face can be taken from the dataset respectively. Face granules are generated pertaining to three levels of granularity. The first 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.

**a. First Level of Granularity**

In the first level, face granules are generated by applying the Gaussian and Laplacian operators. The Gaussian operator generates a

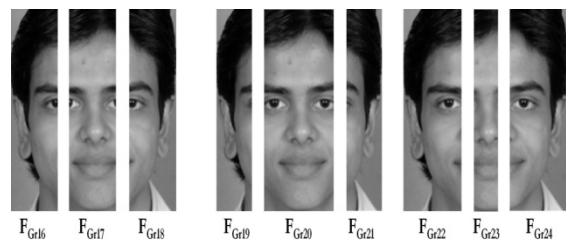
sequence of low pass filtered images by iteratively convolving each of the constituent images with a 2D Gaussian kernel. The resolution and sample density of the image is reduced between successive iterations and therefore the Gaussian kernel operates on a reduced version of the original image in every iteration. Similarly, the Laplacian operator generates a series of band pass images. Let the granules generated by Gaussian and Laplacian operators be represented by  $F_{Gr_i}$ , where  $i$  represents the granule number.

**b. Second Level of Granularity**

To accommodate the observations of Campbell horizontal and vertical granules are generated by dividing the face image  $F$  into different regions



**Figure 5: Horizontal face granules from the second level of granularity**



**Figure 6. Vertical face granules from the second level of granularity**

In the above figure  $F_{Gr7}$  to  $F_{Gr15}$  denote the horizontal granules and  $F_{Gr16}$  to  $F_{Gr24}$  denotes the vertical granules.

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.

### **Phase 2: 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.

#### **a. 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 neighbouring pixels. For computing EUCLBP descriptor the image is first tessellated into non overlapping uniform local patches of size  $32 \times 32$ . For each local patch, the EUCLBP descriptor is computed based on the 8 neighbouring pixels uniformly sampled on a circle of 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  $\chi^2$  distance because it is found to perform better than histogram intersection or log likelihood distance. The idea behind using the EUCLBP features is that the face images can be seen as composition of micro patterns which are invariant with respect to monotonic grey scale transformations.

Combining these micro-patterns a global description of the face image is obtained. In many texture analysis applications it is desirable to have features that are invariant or robust to rotations of the input image. As the LBP patterns are obtained by circularly sampling around the center pixel rotation of the input image has two effects each local neighbourhood is rotated into

other pixel location and within each neighbourhood the sampling points on the circle surrounding the center point are rotated into a different orientation. The main reason for considering uniform patterns is the statistical robustness. Using uniform patterns instead of all the possible patterns has produced better recognition results in many applications.

#### **b. 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 pre-defined 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  $32 \times 32$ . SIFT descriptors computed at the sampled regions are then concatenated to form the image signature. Similar to EUCLBP, weighted  $\chi^2$  distance is used to compare two SIFT descriptors.

### **Phase 3: 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.

1) For selecting feature extractors (type1 chromosome), half of the initial generation (i.e. 50 chromosomes) is set 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.

2) 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.

### **Multi-Objective Firefly Algorithm (MOFA)**

This research learn MOFA algorithm to solve the problem of multi-objective thinking, and its application to the firefly algorithm multi-objective problem solving. Algorithm based on the external feature NP to realize Pareto of multi-objective optimization problem. Below is a basic steps of the algorithm. The population initialization parameters and fireflies position. Initialize external feature NP, and find out all the no dominated Solutions from the initial position of the fireflies filled to the NP.

#### **Ex: Algorithm for Multi objective Firefly Algorithm**

Deal with the final results, the Pareto optimal set the update of the external feature NP using the update strategy. ie, the largest preset

feature (the maximum number of features to retain non-inferior solutions), in an iterative process, when the number of non-inferior solutions feature reaches the specified value, external feature must be maintained the size of the feature, to ensure always does not exceed a fixed value in advance.

### **MULTI-OBJECTIVE EVOLUTIONARY GRANULAR APPROACH**

The proposed granulation scheme results in granules with varying information content. Some granules contain fiducially features such as eyes, nose, and mouth while some granules predominantly contain skin regions such as forehead, cheeks, and outer facial region. Therefore, different feature extractors are needed to encode diverse information from the granules. In this research, any two (complementing) feature extractors can be used; here Extended Uniform Circular Local Binary Patterns (EUCLBP) and Scale Invariant Feature Transform (SIFT) are used. Both these feature extractors are fast, discriminating, rotation invariant, and robust to changes in gray level intensities due to illumination. However, the information encoded by these two feature extractors is rather diverse as one encodes the difference in intensity values while the other assimilates information from the image gradients. They efficiently use information assimilated from local regions and form a global image signature by concatenating the descriptors obtained from every local facial region. The proposed algorithm utilizes the observation that human mind recognizes face images by analyzing the relation among non-disjoint spatial features extracted at multiple granular levels. Further, simultaneously optimizing the feature selection and weight computation pertaining to each face granule allows for addressing the non-linear and spontaneous variations introduced by plastic surgery.

## **4. RESULTS AND DISCUSSION**

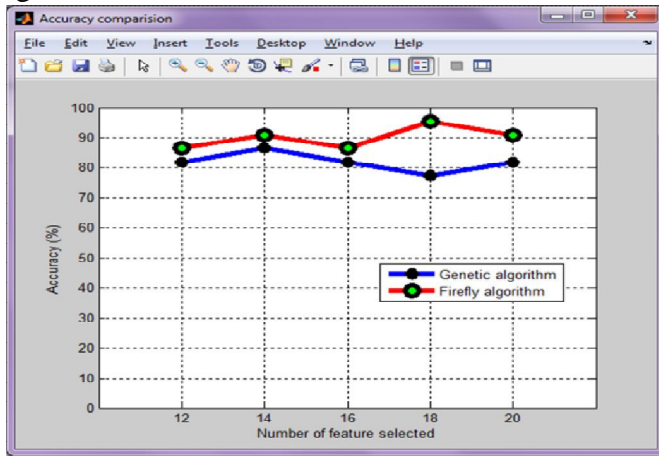
To study the cause of various plastic surgery types on face recognition the proposed algorithm had been selected. The face images before and after plastic surgery were collected from two websites. [www.locateadoc.com](http://www.locateadoc.com) and [www.surgery.org](http://www.surgery.org). The database contains Rhinoplasty (nose surgery), Brow lift (forehead surgery), Otoplasty (ear surgery), Skin resurfacing (skin peeling), Rhytidectomy (face lift) corresponding to local and global plastic surgery full face images that were taken from the above mentioned websites. To calibrate the performance of the proposed algorithm each experiment was performed repeatedly and randomly. The proposed algorithm has the advantage of selecting the better feature extractor and weight for all 40 granules simultaneously for different plastic surgery procedures. The ability to encode local features at different resolutions and sizes allows the proposed algorithm is robust to the nonlinear variations introduced by plastic surgery procedures.

### **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.



The following graph shows the Accuracy comparison for Genetic algorithm and Firefly algorithm.



**Figure 7: Comparison graph for GA and Firefly algorithm**

The above graph in Figure 6.1 shows that the Accuracy comparison of the methods such as Genetic algorithm and Firefly algorithm. The Accuracy is measured in % at Y-axis and methods are depicted in the X-axis. The Accuracy values of the Firefly algorithm for facial feature optimization are higher than the Genetic algorithm. Finally the proposed algorithm of the Firefly algorithm achieves a higher level of the Accuracy value rather than the other algorithm. Thus the proposed system shows higher accuracy performance rate when compare with the existing work.

## 5. CONCLUSION

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 multi-objective evolutionary granular algorithm that 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.

In the present article, Plastic surgery has emerged as a new covariate of face recognition. A novel multi-objective Firefly algorithm called MOFA has been presented. This research presents a multi-objective evolutionary granular algorithm that 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. Further, a multi-objective evolutionary Firefly algorithm is proposed for feature selection and weight optimization for each face granule. The evolutionary selection of feature extractor allows switching between two feature extractors (SIFT and EUCLBP) and helps in encoding discriminatory information for each face granule.

## FUTURE WORK

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. One possible future research direction would be to use thermal-infrared imagery and compute the thermal differences between pre and post surgery images. However, such an approach first requires creating a large face database that contains pre and post operative thermal infrared images.

## REFERENCES

- [1] G. Aggarwal, S. Biswas, P.J. Flynn, and K.W. Bowyer, "A sparse representation approach to face matching across plastic surgery", in Proceedings of Workshop on the Applications of Computer Vision, 2012, pp. 1-7.
- [2] B. Weyrauch, B. Heisele, J. Huang, and V. Blanz, "Component based face recognition

- with 3d morphable models**", in Proceedings of International Conference on Computer Vision and Pattern Recognition Workshop, 2004, pp. 85–91.
- [3] B. Heisele, P. Ho, J. Wu, and T. Poggio, "**Face recognition: component based versus global approaches**", Computer Vision and Image Understanding, vol. 91, pp. 6–21, 2003.
- [4] R. Singh, M. Vatsa, H.S. Bhatt, S. Bharadwaj, A. Noore, and S.S. Nooreydzan, "**Plastic surgery: A new dimension to face recognition**", IEEE Transactions on Information Forensics and Security, vol. 5, no. 3, pp. 441–448, 2010.
- [5] . De Marsico, M. Nappi, D. Riccio, and H. Wechsler, "**Robust face recognition after plastic surgery using local region analysis**", in Proceedings of International Conference on Image Analysis and Recognition, 2011, vol. 6754, pp. 191–200
- [6] S. Mostaghim and J. Teich, "**Strategies for Finding Good Local Guides in Multi-objective Particle Swarm Optimization (MOPSO)**," in Swarm Intelligence Symposium 2003. SIS'03. Indianapolis , Indiana, USA: IEEE Service Center, April 2003, pp. 26–33
- [7] H.S. Bhatt, S. Bharadwaj, R. Singh, and M. Vatsa, "**On matching sketches with digital face images**", in Proceedings of International Conference on Biometrics: Theory Applications and Systems, 2010, pp. 1–7.
- [8] Campbell, X. Li, "**A Non-dominated Sorting Particle Swarm Optimizer for Multi-objective Optimization**," in Proceedings of the Genetic and Evolutionary Computation Conference (GECCO'2003), vol. 2723. Springer, 2003, pp. 37–48
- [9] . A. C. Coello, G. T. Pulido, and M. S. Lechuga, "**Handling Multiple Objectives With Particle Swarm Optimization**," IEEE Transactions on Evolutionary Computation, vol. 8, no. 3, pp. 256–279, June 2004.
- [10] M. Reyes-Sierra and C. A. C. Coello, "**Multi-Objective Particle Swarm Optimizers: A Survey of The State-of-the-Art**," International Journal of Computational Intelligence Research,, vol. 2, no. 3, pp. 287–308, 2006.
- [11] Fayin Li and H. Wechsler, "**Robust part-based face recognition using boosting and transduction**", in Proceedings of International Conference on Biometrics: Theory, Applications, and Systems, 2007, pp. 1–5.
- [12] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "**Face Recognition: A Literature Survey**," ACM Computing Surveys, vol. 35, no. 4, pp. 399-458, 2003.
- [13] S. Samra, S. E. Gad Allah, R. M. Ibrahim, "**Face Recognition Using Wavelet Transform, Fast Fourier Transform and Discrete Cosine Transform**," Proc. 46th IEEE International Midwest Symp. Circuits and Systems (MWSCAS'03), vol. 1, pp. 272- 275, 2003.
- [14] D.-Q. Dai and H. Yan, "**Wavelets and Face Recognition**," in Face Recognition, K. Delac and M. Grgic, Eds. I-Tech, Vienna, Austria, 2007, pp.558
- [15] J. Kennedy and R. Eberhart, "**Particle swarm optimization**," Proc. IEEE International Conference on Neural Networks, pp. 1942-1948, 1995.
- [16] R. C. Eberhart and J. Kennedy, "**A New Optimizer Using Particles Swarm Theory**," Proc. Roc. 6<sup>th</sup> International Symp. Micro Machine and Human Science, pp. 39-43, Oct. 1995.
- [17] Rechenberg, I. J. M. Zurada, R. J. Marks II, and C. Robinson, Eds., "**Evolution strategy, in Computational Intelligence: Imitating Life**", IEEE Press, Piscataway, NJ, 1994.
- [18] Shi, Y. H., Eberhart, R. C., "**A modified particle swarm optimizer**", Proc. of IEEE International Conference on Evolutionary Computation, Anchorage, AK, in press, 1998.
- [19] J. Kennedy and R. C. Eberhart, "**A Discrete Binary Version of the Particle Swarm Algorithm**", Proc. IEEE International Conference on Systems, Man, and Cybernetics, vol. 5, pp. 4104-4108, Oct. 1997
- [20] T. Ahonen, A. Hadid, and M. Pietikainen, 2006. "**Face description with local binary patterns: Application to face recognition**," IEEE Trans. Pattern Anal. Mach. Intell., vol.28, no. 12, pp. 2037–2041.
- [21] Yan Ke, Rahul Sukthankar, 2004 "**PCA-SIFT: A More Distinctive Representation for Local Image Descriptors**", IEEE

Computer Society Conference on Computer Vision & Pattern Recognition, Vol. 2, pp. 506 – 513, 2004.

[22] Bo Wang et. Al, 2013. **“Supply Reliability and Generation Cost Analysis Due to Load Forecast Uncertainty in Unit Commitment Problems”**, IEEE transaction on Power Systems, Vol. 28, no. 3, pp. 2342 – 2252.

[23] Loris Nanni.A Sheryl Brahnam.B et.al. 2011. **“Local Ternary Patterns from Three Orthogonal Planes for human action classification”**, Expert Systems with Applications Vol. 38, pp.5125–128.

[24] Raghavender Jillela and Arun Ross, 2012. **“Mitigating Effects of Plastic Surgery: Fusing Face and Ocular Biometrics”**, Proc. of 5th IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS).