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Feature Extraction Based On Recognition of Surgically Altered Face Images

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Abstract:
In real-world applications, Face Recognition is often impeded with turbulent settings including poses of face images and face expressions. One of the major challenges that have to be converged in face recognition system is the variations caused due to various poses, face expression, illumination, aging and disguise. The allure for plastic surgery as well as its advancement and affordability drives the popularity of plastic surgery procedures. Still there exists difficulty in recognition which includes the nonlinear variations caused due to the plastic surgeries. In order to eradicate the aforementioned statement, this paper emphasizes on face granulation technique, which uses two levels of granularity. Here two feature extractors, Extended Uniform Circular Local Binary Pattern (EUCLBP) and Speeded up Robust Feature (SURF) are used for extracting discriminating information from the face granules. Genetic Algorithm is used to incorporate feature selection and weight optimization for each face granule. Thus with the effective utilization of the aforementioned techniques, matching of pre surgery image with the post-surgery image is done efficiently yielding high identification accuracy.
***Keywords* —** Face Recognition, Face Granulation, Plastic Surgery, Extended Uniform Circular Local Binary Pattern, Speeded up Robust Feature, Genetic Approach.

I. INTRODUCTION

The enchantment for plastic surgery is experienced world-wide mainly due to the advancement in technology and affordable cost. These plastic surgery procedures provide an efficient way to correct and improve the facial appearance for example removing moles, scars. Nowadays, Facial Recognition system is primarily used in security systems, and is comparable to other biometrics like fingerprint, eye iris recognition system etc. In the past only law enforcement agencies were the primary users of facial recognition system. As the system became less expensive, it finds widespread usage with banking, airports etc. This widespread acceptability for authentication systems based on Facial Recognition system has instigated various techniques for evading identification. One such technique is the use of plastic surgery. There are two types of plastic surgeries available as analyzed by Singh et al. [1]. They are local surgery as well as global surgery. Local plastic surgery deals with correcting jaw and teeth, nose structures of the face, as well as chin, forehead, eyelids. Global plastic surgery deals with completely changing the facial structure which is known as full face lift. Such type of non-linear variations introduced by these plastic surgeries remains a great challenge for face recognition algorithms to deal with. As popularity of such plastic surgeries is increasing in today's world due to affordable cost, yet there is no face recognition algorithm to address these variations efficiently.

Singh et al [2] proposed 19 results based on how human mind recognize face images. Humans have the power to identify specific facial features and associate a contextual relationship among them to recognize a face even if the face is altered due to surgeries. Facial Recognition algorithms either process an image of a face either holistically or by separating them into parts. Holistically processing recognition algorithms like PCA, LFA, which plays main role in processing images but those algorithms are not resilience to scale, rotation, and orientation. Besides, it processes face images in a holistic manner which deals with the complete characteristics of a face image.

On the other hand, processing face images as parts, considers several types of information including texture, shape, orientation. In addition, these algorithms plays main role now-a-days when comparing with those algorithms which process images holistically. To provide robustness when proceeding with changes in pose, Heisele et al. [3] proposed component based face recognition approach.

Facial Aging refers to how appearance of face changes with age. Due to Facial Aging skin gets changed with changes in soft tissues of the face. It leads to gradual change in texture of the face. Unlike Aging, plastic surgery is an extemporaneous process and its effects are generally antithetic to that of Facial Aging. Disguise is a means of altering one's appearance to conceal one's identity.

Disguise and Plastic Surgery may be embezzled by criminals to conceal their identities to elude identification. Singh et al [2] evaluated different types of local as well as global surgeries and its effect on Face Recognition algorithms. They addressed that the non-linear variations instigated by plastic surgery procedures are really very hard to be addressed by current face recognition algorithms.

Owing to these reasons, plastic surgery is now established as a challenging covariate of face recognition close to the side of Aging and Disguise. Matching pre surgery images with post-surgery images become laborious work for face Recognition Algorithms. It is our averment that the non-linear variations caused due to plastic surgery; Aging and disguise have some intersection in common. Although there may be variations caused because of this, some features of a face image like center of eye, nostrils and corner of the mouth will never get altered even if plastic surgery or either disguise is performed. So, it is stated that dealing with local regions of the face will yields more efficient outcome when processing an image holistically.

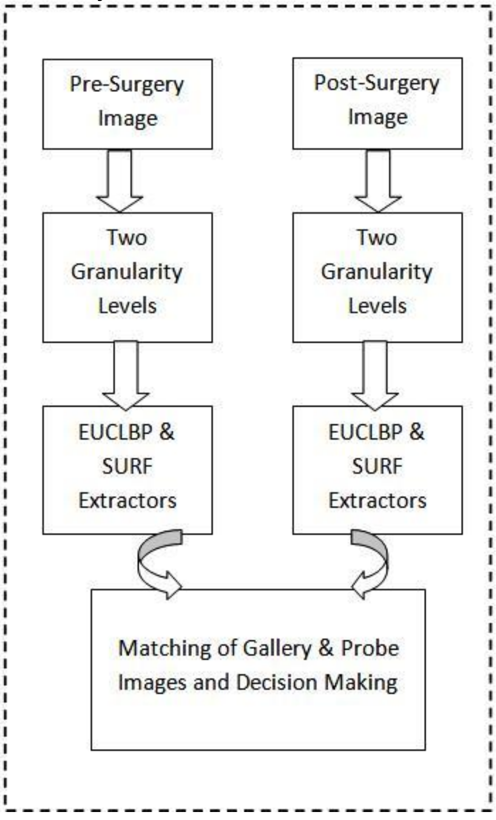

Fig.1: Block Diagram for proposed approach

As shown in Fig.1, proposed approach uses two levels of granularity in which image is divided into face granules which provide resilience to variations in inner and outer facial regions, as well as to address unique features for addressing variations due to plastic surgery. To extract information from these granules two types of extractors are used viz. Extended Uniform Circular Local Binary Pattern (EUCLBP) [5] and Speeded up Robust Features (SURF) [6].

These two extractors will provide diverse information from the face granules. Finally, MultiEvolutionary Algorithm [10] is used for recognizing altered faces due to plastic surgery. This paper is further organized as follows.

Face Granulation with two different levels of granularity and two different types of Feature Extractor as well as Genetic Algorithm is discussed in Section II. Experimental results and conclusions are respectively described in Sections III and IV.

II PROPOSED SYSTEM

A. 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 as observed by Campbell et al [4]. The observations of Singh et al. [1] 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 three different modules. They are,

- Face Granulation
- Feature Extraction
- Genetic Approach

B. Face Granulation

Face Granulation begins with the generation of granules for the face image of size *n x m*. Face granules are generated concerning to two different levels of Granularity.

1. *First Level of Granularity*: In this level of granularity, the face image say, F is divided into horizontal granules (3 face granules per image). By dividing it into horizontal granules this level of granularity provides resilience to variations produced in inner and outer facial regions.

2. *Second Level of Granularity*: In this level of granularity, image F is divided into 9 local regions, thus extracts local facial regions and provides unique features which represent the variations caused due to plastic surgery.

With granulated information, more flexibility is achieved in analyzing information such as nose, ears, forehead, cheeks or combination of two or more features. Multiple features can be analyzed simultaneously using this face granulation scheme. Dealing with the face granules of different sizes helps us to track the local facial features and its effect on plastic surgery procedures.

C. Feature Extraction

The aforementioned face granulation technique is used for extracting face granules which in turn is used to extract facial features. For extracting facial features two feature extractors namely Extended Uniform Circular Local Binary Pattern and Speeded up Robust Features are used. These two extractors are very fast, providing diverse information, and also provide flexibility with rotation and is utmost build robust to changes in gray level intensities. Two extractors are used here, because these two extractors provide discriminating information for each face granule, which yields better performance in face recognition. For some face granules EUCLBP provides more discriminative features than SURF (vice-versa).

1. Extended Uniform Circular Local Binary Pattern (EUCLBP)

Local Binary Pattern [9] is a texture based operator, which provides more robustness to changes in gray level intensities. A central pixel value called the threshold value is compared with the neighboring pixel values which in turn a binary value is assigned to each neighboring pixels. Then the histogram of the labels can be used as texture descriptor. To provide more accurate results, LPB is further extended to use neighborhoods of different sizes and as a result, Circular Local Binary Pattern is evolved.

CLBP is computed based on neighborhood pixels that are well separated on a circle around the central pixel. Another extension to CLBP is the Uniform Circular Local Binary Pattern. Local Binary Pattern is represented as Uniform Local Binary Pattern if it contains at most two bitwise transitions from 0 to 1 or vice versa, when the binary string is considered circular.

For describing facial texture, encoding difference of signs between the neighboring pixels is not sufficient.

Additional useful information's must also be extracted that lies in the difference of gray-level values. Thus as an extension Extended Uniform Circular Local Binary Pattern (EUCLBP) [5] is evolved.

Steps for Extracting Features from EUCLBP:

1. First, the given input image is divided into tessellated image. As a result, patches are obtained.
2. For each patch, the EUCLBP descriptor is computed based on 8 neighboring pixels (radius=2) centered at the current pixel.
3. Exact gray level differences along with difference of sign between neighboring pixels are calculated for each patch.

2. *Speeded up Robust Features (SURF)*

SURF [6] is a scale and rotation invariant descriptor that detects interest points in images. It is a detector-descriptor based approach. SURF detector is based on Hessian matrix and relies on integral images to reduce computation time. The descriptor on the other hand generates a Haar Wavelet response within the interest point neighborhood.

The first step consisting of fixing a reproducible orientation based on information from a circular region around the interest point. Then a square region is constructed aligned to the selected orientation and thus finally features are

extracted from the SURF descriptor. Scale Invariant Feature Transform is also a scale and rotation invariant descriptor which works relatively low when compared with SURF.

The descriptor extracted from the probe as well as gallery image is matched using the following weighted chi square distance measure.

$$x^2(a,b) = \sum_{i,j} w_j \frac{(a_{i,j} - b_{i,j})^2}{a_{i,j} + b_{i,j}} \qquad (1)$$

Where, a and b are the descriptors used for the post-surgery image as well as for the pre surgery image, i and j represents the ith bin of the face granule and jth bin of the face granule, w_j represents the weight for the face granules.

D. Selection of optimum feature selector as well as weights through MultiEvolutionary Approach

Two different types of feature extractors are used, because face granules will produce diverse information which if combined together will yield high performance for face recognition algorithms. So certain feature selection methods are to be incorporated to select features which in turn produce diverse information to be combined for improving the performance. Sequential Feature Selection (SFS) is the widely used selection method which evaluates the growing feature set by adding the features one at a time. Definitive feature selection uses two extractors to extract information but uses dimensionality reduction using PCA to provide with final feature set.

These existing feature selection techniques do not yield high performance when evaluating images for face recognition. So, in order to overcome this issue, Multiobjective Evolutionary approach is used for the selection of optimum feature extractor as well as weights for each face granules. This approach involves searching of large spaces and finding out several sub optimal solutions.

Due to the diverse nature of face granule, its contribution towards recognition accuracy of faces is tremendous. For some face granules, EUCLBP provides better results and for some other face granules SURF yields good performance. But both these extractors used provide discriminating information about the features of the face granules. Thus this MultiEvolutionary algorithm incorporates,

- Selection of optimum feature extractor for each face granule.
- Assigning weights to each face granule.

Genetic Algorithm

In this case, chromosome which is a string whose length is equal to the number of face granule (12 face granules in this case). Two generations with 100 chromosomes are populated. Two types of chromosomes are used here. They are,

- Type1 chromosome
- Type2 chromosome

Type1 chromosome:

Each unit in Type1 chromosome is a binary number (0 or 1) whereas 0 represents EUCLBP descriptor and 1 represents SURF extractor. In the first generation, half of the initial generation (i.e. 50 chromosomes) is set to 1 and remaining 50 chromosomes have the entire unit (genes) as 0.

Type2 chromosome:

Each gene in Type2 chromosome has real valued numbers associated with weights corresponding to the 12 face granules. Weights that are proportional to the identification accuracy of each face granule are used as the seed chromosome. Remaining 99 chromosomes are populated randomly by changing one or more units in the initial chromosome. Three types of operations are performed here. They are,

- Fitness Function
- Cross Over
- Mutation

Fitness Function: Fitness evaluation is performed by selecting feature extractor from type 1 chromosome as well as weight encoded by type 2 chromosomes for each face granule. As a result, 10 best performing chromosomes are selected which is referred as parents to generate the next generation.

Crossover: In order to populate new generation of 100 chromosomes, Uniform Crossover is performed on parent chromosomes.

Mutation: One or more weights of the type 2 chromosome is changed by a factor of its standard deviation in the previous generation in mutation operation, where as in type1 mutation is performed by randomly inverting the units in the chromosomes.

This searching process takes place until the performance of the chromosomes in new generation does not improve when comparing with the performance of the previous five generations. Thus this approach produces the best identification accuracy when compared with the existing algorithms with eliminating the redundant granules which does not support for good identification accuracy.

III.EXPERIMENTAL RESULTS

Thus this proposed method uses Face Granulation which divided an image F into face granules, which is then used by two types of Extractors to extract facial information, from the face granule. An evolutionary genetic approach is used to select optimum feature selector and to assign weights for face granules.

Fig. 2: (a) Horizontal Face Granules, (b) Face granules Using Second level of Granularity

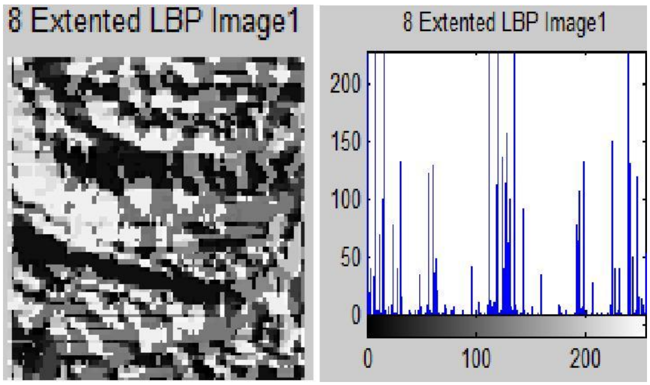

Fig .3: (a) EUCLBP image for the face granule FG8 representing mouth region of the pre-surgery image, (b) Respective Histogram for FG8

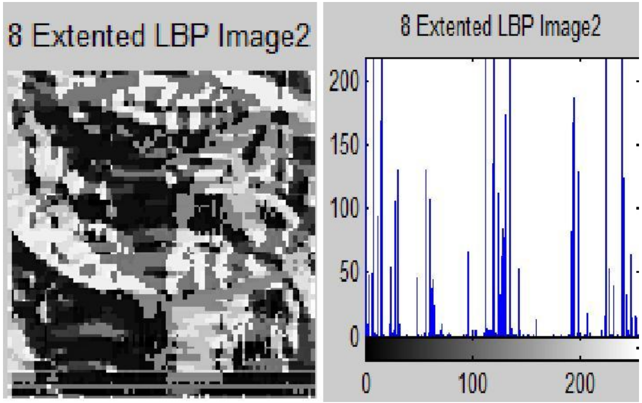

Fig.4: (a) EUCLBP image for the face granule FG8 representing mouth region of the post-surgery image, (b) Respective Histogram for FG8

Fig 2 represents the horizontal face granules as well as the face granules representing the local regions of the pre-surgery image as well as the post-surgery image.On the other hand, Fig 3 & 4 shows the image generated by using the feature extractor EUCLBP as well as its respective histograms for the pre-surgery image and the post-surgery image.

IV.CONCLUSION

This proposed approach deals with local parts of facial region rather than dealing holistically. The image F is first divided into face granules using two different levels of granularity, thus providing resilience to variations caused due to plastic surgeries. Two different types of extractors are used to extract feature information from face granules from different levels of granularity. These two extractors are robust to changes and provide resilience to scale, orientation as well as rotation. A MultiEvolutionary Genetic approach is used to select optimum feature selector as well as to assign weights to the face granules. Thus, it is proved that dealing with local facial regions provides better performance than dealing with holistic images. Thus this proposed approach of matching post-surgery images with pre surgery images provides high identification accuracy when comparing with the existing recognition algorithms.

REFERENCES

[1] R. Singh, M.Vatsa, H.S.Bhatt, S. Bharadwaj, A. Noore, and S. Nooreyezdan, "Plastic Surgery: A new dimension to face recognition*", IEEE Trans, Inf Forensics Security*, vol 5. No 3. Pp, 441-448. Sep 2010.

[2] P.Sinha, B. Balas, Y. Ostrovsky, and R. Russell, "Face Recognition by humans: Nineteen results all computer vision researchers should know about", *Proc. IEEE*, vol.94,no. 11, pp. 1948-1962,Nov. 2006

[3] B. Weyrauch, B. Heisele, J. Huang, and V. Blanz," Component based face recognition with 3d morphable models", in *Proc. Int. Conf. Computer Vision and Pattern Recognition Workshop*, 2004,pp. 85-91.

[4] R. Campbell, m. Coleman, J. Walker,P. J. Benson, S. Wallace, J. Michelotti, and S. Baron-Cohen, "When does the inner-face advantage in familiar face recognition arise and why?", *Vis. Cognit*, vol.6,no. 2, pp. 197-216, 1999.

[5] H. S.Bhatt, S.Bharadwaj, R. Singh and M. Vatsa,"On matching sketches with digital face images", in Proc. Workshop on the Applications of Computer Vision.2012.pp 1-7.

[6] Herbert Bay, TinneTuytelaars, Luc Van Gool, ETH Zurich, "SURF: Speeded up Robust Features", Katholieke University Leuven.

[7] P. Dreuw, P. Steingrube, H. Hanselmann, H. Ney, "Surf-face: Face recognition under viewpoint consistency constraints", In *British Machine Vision Conference,* 2009.

[8] E.Goldberg. Genetic Algorithms in Search, Optimization and Machine Learning. Reading. MA:Addison-Wesley.1989.

[9] T. Ahonen, A. Hadid, and M. Pietikainen,"Face description with local binary patterns: Application to face recognition",*IEEE Transactions on Pattern Analysis and Machine Intelligence,* 28(12):2037–2041, 2006.

[10] F. Vafaee and P. C. Nelson, "A genetic algorithm that incorporates an adaptive mutation based on an evolutionary model", in Proc. Int. Conf. Machine Learning and Applications, 2009, pp. 101–107.