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A New Dimensional Approach towards Fraps-Face Recognition after Plastic Surgery

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Abstract: Increasing popularity of plastic surgery and its effect on automatic face recognition has attracted attention from the research community and many studies were begun towards this area. The nonlinear variations introduced by plastic surgery remain difficult to be modelled by face recognition systems. The variations caused by plastic surgery are long lasting and irreversible. This paper focused on accurately recognizing face images before and after plastic surgery. A face granulation approach is used here. Non-disjoint granules of face images are generated. The face granulation scheme helps in analyzing multiple features simultaneously. Moreover the granulation approach helps to gain significant insights about the effect of plastic surgery procedures on different facial features and in the neighboring regions. In this approach face granules are generated pertaining to three levels of granularity. Two popular 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. BAT algorithm is used to match face images before and after plastic surgery. This approach provides the advantage of choosing better performing feature extractor for each face granule. This algorithm helps in discarding redundant and non discriminating face granules and achieving high identification accuracy.

Keywords: EUCLBP, SIFT, BAT algorithm

I. INTRODUCTION

Face recognition has emerged as one of the most extensively studied research topics that span multiple disciplines due to its numerous important applications in areas like identity authentication and security access control. The success of any face recognition methodology depends heavily on the particular choice of the features used by the classifier. The selected features should be the most discriminate features which are not sensitive to arbitrary environmental variations such as variations in pose, scale and illumination.

Plastic surgery changes the shape and texture of facial features to varying degrees. Both corrective and cosmetic surgeries alter the original facial information to a large extent thereby posing a great challenge for face recognition algorithms. A face granulation approach is used in this project. Non-disjoint granules of face images are generated. Each granule represents different information at different size and resolution. The face granulation scheme helps in analyzing multiple concurrent features simultaneously. In this approach face granules are generated pertaining to three levels of granularity. Two popular feature extractors namely Extended Uniform Circular Local Binary pattern and Scale Invariant Feature Transform are used for extracting discriminating information from face granules. Responses from the face granules are unified in an evolutionary manner.BAT algorithm is used to match face images before and after plastic surgery. This approach provides advantage of choosing better performing feature extractor for each face granules and achieving high identification accuracy.

II. RELATED WORK

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

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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. Several part based face recognition approaches capture this observation for improved performance. The component based face recognition approach using different facial components provides robustness to pose[8]

Another algorithm uses gray-level pixel values. The information from several facial components were concatenated and classification was performed using SVM. In another approach local patches were extracted from different levels of Gaussian pyramid and are arranged in an exemplar manner. These exemplar based-local patches were then combined using boosting to construct strong classifiers for pre-diction. In another approach a subset selection mechanism was proposed where the most informative local facial locations were used in decision making. Surgical procedure may lead to alterations in more than one facial regions. They recognize faces using a combination of holistic approaches together with discrete levels of information. The inner and outer facial regions represent distinct information that can be useful for face recognition[2] A multiobjective genetic algorithm is used for recognizing the surgically altered face images[1]

III. PROPOSED WORK

In the proposed system a granular computing approach is used. The proposed system uses a multiobjective evolutionary granular computing. When an individual undergoes plastic surgery facial features are reconstructed either globally or locally Two popular feature extractors namely Extended Uniform Circular Local Binary Pattern and Scale Invariant Feature Transform are used for extracting discriminating information from different face granules. Every face granule has useful but diverse information which if combined together can provide discriminating information for high level face recognition. Some facial regions are more discriminating than others and hence contribute more towards the recognition accuracy.

The proposed system optimizes the identification process by discarding redundant and non discriminating face granules .It can provide solution to non linearity problems introduced by plastic surgery. It can consider multiple concurrent features which leads to high level face recognition. It shows better performance in matching surgically altered face images against large scale gallery. With granulated information more flexibility is achieved in analysing assimilated information from face images. Multiobjective evolutionary approach with BAT algorithm offers solutions that both significantly improve the computation time and yield reasonably accurate identification results in high dimensional data analysis.

IV. SYSTEM DESIGN

A . Face image granulation

In the granular approach non disjoint features are extracted at different granular levels. With granulated information more flexibility is achieved in analyzing underlying information such as nose, ears, forehead, cheeks and combination of two or more features. Granulation scheme helps to gain significant insights about the effect of plastic surgery procedures on different facial features and their neighbouring regions. Let F be the detected frontal face image of size $n \times m$. Horizontal and vertical granules are generated by dividing the face image F into different regions[4]. In the following figure, face granules from 7to 15 denotes the horizontal granules and 16 to 24 denotes the vertical granules..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.Second level of granularity helps to analyze different combinations of local features that provide resilience to concurrent variations introduced in multiple regions.

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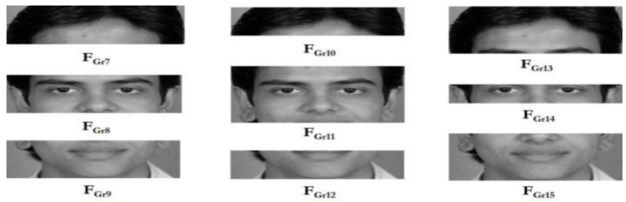

Figure1:Horizontal face granules

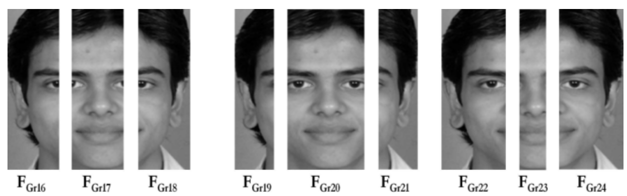

Figure2:Vertical face granules

B. Feature extraction

The feature extraction process can be defined as the procedure of extracting relevant information from a face database. This information should be valuable to the later steps of identifying the subjects with an acceptable error rate. The extracted features should be efficient in terms of computing time and memory usage. This process creates new features based on transformations. Two popular feature extractors are used to extract discriminating features from different face granules. They are Extended Uniform Circular Local Binary Patterns and Scale Invariant Feature Transform. The proposed granulation scheme results in granules with varying information content. Some granules contain fiducial 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.

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 × 32. For each local patch, the EUCLB descriptor is computed based on the 8 neighbouring pixels uniformly sampled on a circle of radius 2 cantered at the current pixel. The concatenation of descriptors from each local patch constitutes the image signature .Two EUCLBP descriptors are matched using the weighted χ^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 canter 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.

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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 uses 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 predefined interest points.In this approach SIFT descriptor is computed in a dense manner over a set of uniformly distributed non overlapping local regions of size 32×32.SIFT descriptors computed at the sampled regions are then concatenated to form the image signature.Similar to EUCLBP weighted χ^2 distance is used to compare two SIFT descriptors too because of its performance.For any object in an image interesting points on the object can be extracted to provide a feature description of the object.This descriptions extracted from a training image can then be used to identify the object when attempting to locate the object in a test image containing many other objects.

C. Feature selection using BAT algorithm

Feature selection attempts to find the most discriminative information in several application domains. It is often desirableto find features that are simple to extract, invariant to geometric and affine transformations, insensitive to noise and also usefulfor characterizing patterns in different categories. The choice of such features is a critical step and strongly depends on the nature of the problem.. Bat Algorithm (BA) is a whether a feature will belong to the final set of features or not. The function to be maximized is the one given by a supervised classifier's accuracy. As the quality of the solution is related with the number of bats, we need to evaluate each one of them by training a classifier with the selected features encoded by the bat's position and also to classifying an evaluating set. There are many reasons for the success of bat-based algorithms. By analysing the key features and updating equations, we can summarize the following three key points/features:

• Frequency tuning: BA uses echolocation and frequency tuning to solve problems.Though echolocation is not directly used to mimic the true function in reality,frequency variations are used. This capability can provide some functionality that may be similar to the key feature used in particle swarm optimization and harmonysearch. Therefore, BA possess the advantages of other swarm-intelligence-basedalgorithms

• Automatic zooming: BA has a distinct advantage over other metaheuristic algorithms. That is, BA has a capability of automatically zooming into a region where promising solutions have been found. This zooming is accompanied by the automatic switch from explorative moves to local intensive exploitation. As a result, BA has a quick convergence rate, at least at early stages of the iterations, compared with other algorithms.

• Parameter control: Many metaheuristic algorithms used fixed parameters by using some, pre-tuned algorithm-dependent parameters. In contrast, BA uses parametercontrol which can vary the values of parameters (A and r) as the iterations proceed. This provides a way to automatically switch from exploration to exploitationwhen the optimal solution is approaching. This gives another advantages of BAover other metaheuristic algorithms.

1. All bats use echolocation to sense distance, and they also 'know' the difference between food/prey and background barriers in some magical way;
2. Bats fly randomly with velocity vi at position xi with a fixed frequency fm in, varying wavelength and loudness A0 to search for prey. They can automaticallyadjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission r 2 [0, 1], depending on the proximity of their target;
3. Although the loudness can vary in many ways, we assume that the loudness variesfrom a large (positive) A0 to a minimum constant value Amin.Another obvious simplification is that no ray tracing is used in estimating the timedelay and three dimensional topography. Though this might be a good feature for the application in computational geometry, however, we will not use this as it is more computationally extensive in multidimensional cases. In addition to these simplified assumptions, we also use the following approximations, for simplicity. In general the frequency f in a range

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[fmin, fmax] corresponds to a range of wavelengths [_min, _max]. For example a frequency range of [20kHz, 500kHz] corresponds to a range of wavelengths from 0.7mm to 17mm. For a given problem, we can also use any wavelength for the ease of implementation. In the actual implementation, we can adjust the range by adjusting the wavelengths (or frequencies), and the detectable range (or the largest wavelength) should be chosen

Algorithm1. Pseudo Code of BAT Algorithm

1) Objective function: f(x), x=(x1,….xd)t
2) Initialize bat population xi and velocity vi i=1, 2 ,..n
3) Define pulse frequency fi at xi
4) Initialize pulse rate ri and loudness Ai
5) while (t<maximum number of iterations)
6) Generate new solutions by adjusting frequency, and updating velocities and location/solutions.
7) F (rand> ri)
8) Select a solution among the best solutions
9) Generate a local solution around the selected best solution
10) end if
11) if (rand< Ai and f(xi)< f(x*))
12) Accept new solutions
13) Increase ri, reduce Ai
14) end if
15) Ranks the bats and find current best x*
16) end while
17) Display results.

D. Matching of face granules

Face granules are combined with multiobjective evolutionary learning for accurate face recognition.The granular approach for matching faces altered due to plastic surgery is summarized below

1) For a given gallery-probe pair several face granules are extracted from each image.
2) EUCLBP or SIFT features are computed for each face granule according to the evolutionary model learned using the training data.
3) The descriptors extracted from gallery and probe images are matched using weighted X^2 distance measure.The weighted χ^2 distance is found to perform better than histogram intersection or log likelihood distance.

$$X^2(a,b)=\sum_{i,j} w_j \{(a_{i,j}-b_{i,j})^2/(a_{i,j}+b_{i,j})\}$$

where a and b are the descriptors computed from face granules pertaining to a gallery-probe pair i and j correspond to the i^{th} bin of the j^{th} face granule and j is the weight of the j^{th} face granule.
4) In identification mode (1: N), this procedure is repeated for all the gallery-probe pairs and top matches are obtained based on the match scores.

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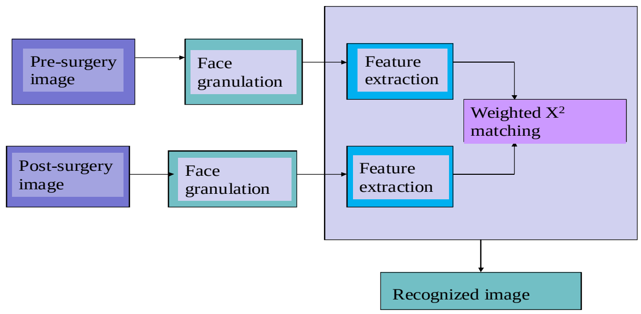

Figure 3:Overall architecture of the system

This approach takes the presurgical images as input and accurately identifies the surgically altered face images.It shows better identification accuracy.

Sample input set

Figure 4:Variation in facial appearance due to plastic surgery

Sample output

Figure 5:Recognized face image

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V. EXPERIMENTAL RESULTS

In this section we discuss the experiments conducted in order to assess the robustness of the Bat Algorithm for feature selection. In regard to the datasets, we have employed five public datasets: Breast Cancer, Australian, German Numer, DNA and Mushrooms.

NUMBER OF FEATURES SELECTED FOR EACH OPTIMIZATION TECHNIQUE

Dataset	BA	PSO	FFA	HS	GA
Australian	8	12	12	9	12
BreastCancer	7	8	7	7	8
DNA	18	25	75	67	28
GermanNumer	7	4	5	19	3
Mushrooms	53	76	106	106	57

The abouve table displays the number of selected features for each optimization technique. It is interesting to shed light over that BA has selected fewer samples than all techniques,except for German Numer dataset.

CLASSIFICATION ACCURACY WITH THE BEST SUBSET OF FEATURES

Dataset	BA	PSO	FFA	HS	GA
Australian	77.25	76.12	76.63	76.53	76.12
BreastCancer	96.31	94.28	92.85	94.23	95.74
DNA	83.02	79.31	76.63	83.23	81.46
GermanNumer	70.24	59.52	53.41	55.24	70.87
Mushrooms	100.0	99.96	100.0	99.95	100.0

VI. 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. 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. The proposed algorithm utilizes the observation that human mind recognizes faces by analyzing the relation among non-disjoint spatial features extracted at different granularity levels. Experiments under different protocols including large scale matching, show that the proposed algorithm outperforms existing algorithms including a commercial system for matching surgically altered face images. Further studies on several local and global plastic surgery procedures also show that the proposed algorithm consistently outperforms other existing algorithms. Detailed analysis on the contribution of granular levels and individual face granules corroborates the hypothesis that the Bat algorithm unifies diverse information from all granules to address the non-linear variations in pre and post surgery images and have high degree of identification accuracy.

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