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CHALLENGES AND EFFECTS OF PLASTIC SURGERY ON FACE RECOGNITION PERFORMANCE: A REVIEW

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ABSTRACT

This paper demonstrates the different classifications of plastic surgery and different processes that are conducted in this area. The paper surveys on the research approaches when it comes to plastic surgery problems and the various categories the methods can be classified into. It discusses the difference between holistic approaches and local region based approaches and the way fusion based methods can take the best elements of both features as holistic response and local region based response has very little correlation amongst themselves.

KEYWORD: Systematic Review, Systematic Review, Ethics, Principles, Plastic Surgery, Principles, Plastic Surgery.

1. INTRODUCTION

Human Face Recognition (HFR)[1] is a ubiquitous avenue in the field of Biometric Recognition.[2] Like other human identification areas including signature, fingerprints, iris and gesture, human faces too serves as an important area for the purposes of verification and identification. It has also plenty of uses when it comes to e-commerce applications.[3] Humans are experts when it comes to recognizing faces of individuals and associating such faces with the correct person. In fact they are more likely to recognize a face correctly than the name of the person. Even though every person has the same components such as eyes, nose, ears and mouth, humans are very sensitive in distinguishing the fine characteristics of a face. This is attributed to the fact that humans are visually more developed. Our brains have highly specialized regions when it comes to processing visual information as compared to other types of information. However problem arises with the rise in scale of images that far exceeds the appropriate time to be spent for manual processes. Therefore there is a need for automation when it comes to facial recognition.

The objective of an automatic facial recognition system is to develop a model that can replicate the accuracy of a real human with the speed of automation. A good HFR system will rightly associate the correct images with the correct individuals. However several challenges arise that a HFR algorithm has to tackle. It includes pose, illumination variation, occlusion, aging and expression. While plenty of research is already done into these areas[3-11], there is a new challenge that contest the performance of these algorithms: *Plastic Surgery*.[12]

Plastic surgery is a process of transforming some of the facial features to remove scars, marks, birth marks, injuries caused due to accidents or fatalities. It is also used for cosmetic purposes and aesthetic purposes. Whichever the purpose, the result lies in the face being modified even if it is to the slightest amount. Such facial transformations often lead to some key challenges. The impact of plastic surgery is getting more and more prevalent. According to the American Society for Aesthetic Plastic Surgery for year 2008[13], it has been established that people of the age of 19-65 undergoes over 90% of plastic surgery deeming it quite popular. Also there has been an immense surgery in the rate of plastic surgeries since the start of the century till now. This may be due to various factors from medical to social. This increase poses two critical problems in the field of face recognition that former methods of the field faces:

- ***Ineffective Identification***

Increase in plastic surgery will result in the ineffective biometric identification and verification due to the change to facial features. This will seriously result in enormous inaccuracies that can hurt the financial sector like the banking services where facial recognition is an important form of identification. Something as small as cosmetic surgeries can cause an enormous dip in the performance of existing facial recognition systems. In[14], it has been shown that various established methods[15-17], in the field of face recognition falters tremendously when it comes to tackle plastic surgical face recognition.

- ***Security Threat***

This is probably more sinister of a problem than the previous one. A criminal can get away with his crime and avert a security identification process thereby leaving the investigation system in jeopardy. A criminal can undergo modifications in his facial structures or features to bypass the facial recognition systems and thereby bypassing biometric identification. Such a potential threat is enormous and the algorithms produced must be equipped to tackle this problem. The South Korean customs incident exemplifies this.[18]

Unfortunately, there hasn't been enough scientific study and analysis conducted on any constructive mechanism that can effectively tackle this problem. There are mainly two basic reasons for this: *Construction of an efficient database* – Since occasions revolving plastic surgery essentially involve tragedies like accidents or fatal conditions and even social challenges or people trying to cover up their discreet diseases, there is an element of privacy attached to it. People who have undergone such processes do not want to share their images and this becomes one of the biggest problem in preparing a good database for the algorithms to work upon. While challenges like pose, illumination variation and expression have well established databases for efficient algorithms, plastic surgery has an immense setback in that. Secondly *Facial Geometric Transformations* – Since plastic surgery is inherently a facial transformation and reconstruction methods, there is a change in geometric relationships between facial features like the width or length of a nose, changes in sections of the cheek, etc. Changes in such geometric patterns of the face present a high probability of inaccuracies that the established facial recognition algorithms face.

Now, there are various types of plastic surgery in the field of surgery. *Section 2* describes the type of plastic surgeries and the challenges it avers.

2. VARIOUS TYPES OF PLASTIC SURGIES

Every plastic surgery procedure has one thing in common: they all undergo some sort of facial transformation and deviates from the normal. Plastic surgery is categorized into two types of classification.

A. CLASSIFCATION BY REGION OF IMPACT

This type of classification category establishes the degree to which a plastic surgical procedure impacts. It is based on the transformation of features and the scale of it. Plastic Surgery under this kind of classification is of the following types:

- ***Local Plastic Surgery***

Surgical procedures falling under this category usually has a small range of impact and is localized to certain regions of the face. Local Plastic Surgery is done primarily to correct anomalies occurred at birth, marks obtained due to some accidents or for cosmetic purposes. This would involve modifications of certain areas of cheeks, or the slight modifications on the nose, forehead or eyelids. Although procedures undergoing this type of surgery does some facial modifications, the modifications are mainly concentrated on certain areas of the face. The overall structural composition of the face visibly appears same, i.e. there is no overall change in the facial structural components on the whole. It is therefore apparent that recognition methods can do fairly well in this category compared to the following category. However local plastic surgical methods can cause more challenge if more than one type of modification occurs in the face or there is a coalescence of different procedures. In that case the recognition accuracies of algorithms will fall significantly.

- ***Global Plastic Surgery***

Surgical procedures falling under this type of category usually has an enormous impact on the face as it refers to the whole face and not just any particular region. Global plastic surgical procedures undergoes a complete face lift of the face. There is complete facial reconstruction of the face. Such a surgical procedure is done mainly to cede to damages caused by fatal accidents or burns. Therefore facial reconstruction of such scale usually ends up in changing the whole geometric feature pattern of the face. The new face formed is usually has a significant difference to the original face. This may involve change in the color, change of critical regions of interest and new geometric relationships are formed between the facial features. This seriously affects the recognition accuracies of facial recognition procedures and can be severely misused by criminals looking to bypass security identifications. Compared to the local plastic surgical effect, this type of surgery affects the face tremendously.

B. CLASSIFICATION BY SURGICAL PROCEDURE

This type of classification category is based on the type of medical surgeries performed and is purely based on the process. Novel algorithms can be created addressing a particular type of plastic surgery. The following categories in Fig. 1 demonstrate the full range of such processes.

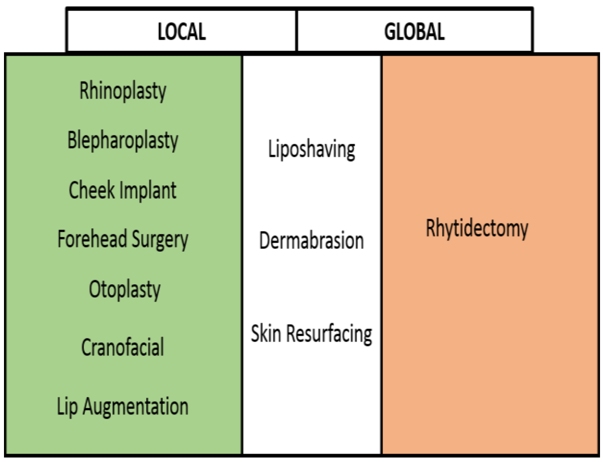

Fig. 1. Types of Classification of Plastic Surgery Procedures

- ***Eyelid Surgery (Blepharoplasty)***

This is primarily modifying defects and anomalies on the eyelids. It includes reconstruction of the eyelids covering the area from the eyebrows to the upper cheek area.[19] It is more prevalent amongst women. It can be seen in Fig. 2.

- ***Forehead Surgery (Browplasty)***

This is usually done to lift a sagging forehead skin that comes in the line of sight and affect the vision.[20] Usually occurring due to aging, browplasty, is more prevalent amongst the older age.

- ***Chin Surgery (Genioplasty)***

Usually involves in addition of material to the chin or removal of it, it is done by repositioning the jaw bone or by adding different materials like silicone and polyethylene to the chin.[21]

- ***Nose Surgery (Rhinoplasty)***

Nose surgery is the type of plastic surgery performed on the nose. It is generally the shaping or the restructuring of the nose. Rhinoplasty can be done both as function surgery caused due to trauma or burns or a cosmetic surgery.[22] It is mostly done for aesthetic purposes like changing the proportions of the nose with the mouth. There are also non-surgical methods for Rhinoplasty. Genioplasty often follows Rhinoplasty though not in all cases.

- ***Ear Surgery (Otoplasty)***

Ear surgery involves the correction of birth marks or anomalies occurring the region of external ear or the pinna.[23] It can be both surgical and non-surgical in nature. It can be caused due to aesthetic purposes or functional purposes like trauma, burns, etc. It involves restructuring of the size of the pinna and the angles of the ear with respect to the head. It can be seen in Fig. 2.

- ***Cheek Augmentation***

Primarily used for cosmetic purposes like Genioplasty, this involves addition of materials on the cheekbone or the middle of the cheeks giving for an elevated or a concave look respectively. The main material used like Genioplasty is silicone.

- ***Lip Augmentation***

Lip Augmentation is mainly used for cosmetic purposes. It involves addition of material in enhancing the structure of the lips for facial betterment.[24] Filler Implants like Autologen, Collagen, etc. are added to enhance and modify the lip structure according to preference.

- ***Liposhaving***

Essentially this is a fat removal process[25] that accumulates under the chin, resulting in a dual chin appearance or neck contouring. Mainly used for aesthetic purposes, but can be furthered to counteract excess fat disorders.

Fig. 2. (Top) Otoplasty, (Middle) Blepharoplasty, (Bottom) Rhytidectomy

- ***Skin Peeling (Resurfacing)***

This is a global type of surgery used for rejuvenation of the entire face by the use of laser technology[26] or chemicals to remove sagging skin or wrinkles which are basically used for de-aging purposes. This type of surgery results in changes of the geometric relationships of the face and gives the face a younger look.

- ***Craniofacial Surgery***

This type of surgery deals with facial structures as in the bones and skin rather than soft tissues. It is primarily used to remove birth defects in areas such as ears, jaws or the skull.[27] It is usually done to infants or toddlers as it deals with anomalies occurred at birth.

- ***Face Lift (Rhytidectomy)***

A face lift is a full changeup of the facial features like facial toning or removal of unwanted skin on the face. It can be composed of a variety of other procedures[28] and is a global plastic surgery in nature. It can be used for both aesthetic or functional purposes like trauma, face burns, accidental deformations. It can also be used for de-aging purpose. This changes critical geometrical features and causes serious decline in the feature relationships of the face. An example is shown in Fig. 2.

- ***Dermabrasion***

It is used for smoothening of the texture of skin by reaching the deepening layers. It involves covering of sunburns, abrasions, infections, herpes, etc. It can be conducted on certain areas of a face or to the entire face.

From Fig. 1, we can see that only Rhytidectomy is entirely global plastic surgery while Rhinoplasty, Blepharoplasty, Otoplasty, Craniofacial, Lip Augmentation and forehead lift are all local surgical procedures. Liposhaving, Dermabrasion and Skin Peeling can be applied to both local regions of the face or to the entire face. The two type of classification categories give us a better insight into the categories of problems that can arise.

3. RESEARCH APPROACHES TO PLASTIC SURGERY

Since plastic surgery is an extremely new avenue of facial recognition challenges, there are not many techniques that can tackle such problems. This paper throws lights on methods that have been used on plastic surgery databases to whatever effect. Research on this field has followed two directions.

- ***Classification Methods***
- ***Database Construction***

Both these directions are relatively unexplored and has enormous potential to discover. The biggest challenge is establishing methods that can tackle this classification problem. The following subsection organizes the different types of methods used on plastic surgery databases.

I. CLASSIFICATION METHODS

A. Appearance Based Methods

These methods involve the use of an example images as templates for the use of recognition. Typically they can be in the form of subspace projections.

The Principal Component Analysis (PCA)[31] is a subspace learning method where a training set is obtained by taking few images as input vectors. The space formed by the eigenvectors becomes the eigenspace also known as the projection space. Both the training and the test are projected using this projection space and the minimum Euclidean distance of the projected vectors are obtained for classification. In[29-30], PCA was used on a plastic surgery database where its accuracy was around 30% compared to its double accuracy on non-surgical databases. PCA is has a higher recognition rate amongst Otoplasty images in Local Surgery but its recognition rate amongst other categories of images are around its overall accuracy rate of 27%. It is also the least efficient recognition method.

The method proposed by Fisher Discriminant Analysis (FDA)[31] is based on subspace learning method where the objective is to find a linear combination of features that separates different classes of images. It involves maximization of between class scattering and minimization of intra class scattering. By doing so, it can cluster points belonging to similar classes together while maximum separation between the classes of points. Unlike the PCA which does not take into account the difference between the classes, FDA considers that. The test set is projected on the eigenspace formed by the eigenvectors considering the between class covariance matrix. FDA was used on both plastic surgery database and non-surgical database. It produces slightly better results than PCA with over 30% accuracy on surgical database. Here too the recognition accuracy on non-surgery database is double the accuracy on surgical database. It also shows similar characteristics to PCA when it comes to different types of plastic surgery.

Marsico et.al[43] has demonstrated two appearance based methods like Face Recognition Against Occlusions and Expression Variations (FARO)[44] and Face Analysis for Commercial Entities (FACE)[45] on plastic surgery images as a better alternative to the PCA and FDA methods. The algorithm is based on similarities between local Regions of Interest which are used for experimentation. FARO is fractal based method which locally estimates Partitioned Information Function Systems (PIFS) information for facial regions like eyes, mouth, etc. PIFS self-similarities are formed into feature vectors and ad hoc distance measure is used for facial recognition performances. FACE on the other hand is a co-relation based method involves a measure known as the correlation index amongst sub regions in an image and amongst different images. Sub regions in similar positions amongst different images are compared for maximum correlation. The local maxima are aggregated to form a global correlation. Face recognition is performed based on this correlation index. FARO is better than PCA and FDA but suffers from illumination variants as a limitation of fractals and thereby it suffers problems which are not necessarily just based on surgical deformations but different lighting conditions on those deformations. FACE on the other hand is computationally expensive but a superior method to FARO and significantly better than conventional PCA and FA.

B. Feature Based Methods

The methods that follow this approach involve in extracting relevant and important features from the face or an object like proportions of the nose, eyes, position of the mouth with respect to the nose, etc. and compare them with similar position features of another object or face for recognition purpose. It may also involve features in similar positions of faces which are used for recognition purpose.

The Local Feature Analysis (LFA)[32] is a featured based method by obtaining the fiducial points of a facial image after which the dense local characteristics of the face at a point which are matched to the second order statistics of the input set and creating maximum variance with the output classes. The next order correlations are used to rarefy the outputs thereby obtaining the low-dimension reduction representations and de-correlate such representations. Such representations of the face and matched with the training set for recognition based on a local based representation. This feature based method demonstrates a 40% recognition accuracy when conducted on plastic surgery databases which is a 30% drop-off when compared to its non-surgical counterpart. Interestingly when dealing with eyelid surgery images it measures same recognition rates with skin peeling (global process). Like previous methods it demonstrates maximum recognition when it comes to Otoplasty images.

Speed-Up Robust Features (SURF)[40] is a rotation invariant feature detector and descriptor. The algorithm uses a detector using the Hessian Matrix as the base and the points where its determinant maximizes are considered interest points. It is multi-scale efficient as it uses integral images to form them thereby enormously reducing the time process. Now these points known as the interest points a need a descriptor to describe what feature they represent. It uses a wavelet filter to describe the feature vector at those points. The orientation around the interest points is obtained by dividing the region into sub region and getting the Haar wavelet response of those sub-regions. The resultant is a rotation invariant feature descriptor. Minimum distance is used to obtain recognition accuracy. However when it comes to plastic surgical images, it gives a mere 50% accuracy even though it achieves the highest recognition rate amongst conventional methods when it comes to local plastic surgical images.

A better feature based method which has been developed of late is which is based on the Near Sets Theory[33] which involves obtaining features values from physical components of the facial images such as nose length, width of the eyes, distance from the mouth, etc. Faces or Objects with similar feature values are grouped together in a set. Near sets require objects comprising common feature values to be closely matched while others to farther apart. In Patnaik et. al[34], near sets were used to determine the qualitative similarity correspondence between the pre-surgical and the post-surgical images. Disjoint sets were similar to each other only which there are shared feature values amongst them and the degree to which they bear similarity is the nearness measure. It was employed on *blepharoplasty* and *Otoplasty* images because of their pervasive prevalence. A better formation of a nearness measure can be used for enhancing recognition accuracies. It was also discussed in[35] where three features including the nose length (NL), nose width (NW) and eyeball distance (EBD) were being used for the nearness measure amongst other feature elements of both sets of images. Two approximations are generated from which the boundary region is obtained relative to neighborhood of selected feature as a Near Set.

Singh et.al[52] proposed a facial recognition method based on the theory of Rough Neural Network (RNN). Rough sets basically help is discerning the relation that can separate maximum number of points between classes. It is a fast process and is decision table based method used for classification rules. RNN is used for classification purpose.

Ting et.al[53] proposed a facial recognition method based on prediction. Landmarks on the face are detected using regions of interest and distance vectors are produced from it. Frontal images are taken as the inputs. The vectors are learned using Support Vector Regression (SVR) or k-nearest neighbor (KNN) which is trained on former sets of pre-surgical and post-surgical image distance vectors. Landmark positions are updated and they are generated based on the changes between the original vectors and the predicted ones. This method is better than any conventional face recognition algorithms when it comes to plastic surgeries and produce high rank-1 accuracy rates.

C. Texture Based Methods

Approaches to face recognition used this school involves the use of local facial texture to obtain change invariant features that gives better recognition accuracies. Generally texture based methods involves breaking up of the image into regions or blocks and obtaining features that retain the local characteristics of that region or block.

The Circular Local Binary Pattern (CLBP)[36-37], is a textured based method that uses a global texture description LBP operator that assigns each neighborhood a binary string based on the center pixel intensity value. If a pixel in a 3x3 neighborhood is having a value greater than the center pixel intensity then 1 is assigned otherwise 0. In this way all the 8 pixels in a 3x3 neighborhood are assigned a binary value and the binary string is obtained by taking those values in a circular order. This is a local characteristic feature and CLBP gives a general texture description of an image. LBP features are compared for recognition purpose. LBP has almost 50% recognition rate on plastic surgery images while having around 75% recognition rate on non-surgical images. It has a lesser drop off than the previous methods save near sets. Even though it performs significantly more in local surgical processes, like on Otoplasty, it has a fair global recognition accuracy which is quite higher than LFA, FDA or PCA. Another texture based approach is the 2-D Log Polar Gabor Transform using a Neural-Network Approach (GNN).[38] It uses a neural network for optimizing the result of a Gabor transform to extract textural information based on its phase. Here the initial image is sampled as a logarithmic function of its distance from the center after which a Gabor filter is used for the extraction of amplitude and phase feature from the polar transform of the image. During learning Neural Network is used to combine the discriminative and unique features of the log polar Gabor transform for optimized recognition purpose. In case of plastic surgery it performs better than the CLBP process. However it faces a bigger drop off of around 35% from non-surgical to surgical dataset. Overall amongst the conventional method this outperforms the others with over a 70% recognition rate for Otoplasty images and over 50% for skin peeling images. It also does relatively better for blepharoplasty and forehead lift images.

D. Fusion Based Methods

Singh et.al in[30] demonstrated that the Pearson Correlation coefficient between the holistic algorithm response and the local feature based or texture based algorithm response were minimal. It suggested that the two responses were different in nature and there could have been a possibility of fusing these two nature of methods could yield a highly discriminative response which could prove competence when dealing with pre-plastic surgery and post-plastic surgery images.

Himashu et.al in[41] suggested an evolutionary algorithm based on the observation that the human face has several features possessing a contextual relationship amongst them. It proposed generation of non dis-joint granules each having information at various resolutions. UCLBP and SURF are used to detect discriminative information from the informative facial granules. Genetic Algorithm is used to combine the responses of UCLBP and SURF. It establishes three levels of granularity with each top layer having a more holistic information while the lower tier granules having a more local based information. The top level granules are obtained by using a kernel function of the highest resolution while the lower level granules preserves the unique relationships amongst granules which gives it an unique discriminative factor. UCLBP is used for dimension reduction and obtaining the rotation invariant features from the granules and SURF is used for determining features based on the spatial distribution of gradient information around the interest points. The weighted χ^2 distance measure is used for facial recognition performance and the weights are obtained used a Genetic optimization Algorithm which is an evolutionary learning method. The method outstrips conventional face recognition algorithms and it possess a near 80% accuracy when it comes to pre-surgical and post-surgical databases. It is also proven to possess a better score when compared with Granular UCLBP or Granular SURF. The fusion clearly indicates that the method uses highly discriminative factors from both methods.

Gaurav et.al[45] proposed a part-wise approach on sparse representation of facial features which banks on the number of features more important than the choice of features themselves.[46] It bases upon the fact that during plastic surgeries not all parts of the face goes severe transformation. The algorithm at first locates primary facial features using an iterative facial landmark detector called STASM.[47] A training matrix is generated using standardized PCA for characterizing each facial part. The matrix is arranged in a class wised submatrices. It then generates a sparse coefficient vector is obtained and recognition is based on which class within the training matrix best represents the test data sample. A sum rule based fusion is performed to obtain the best results from all facial parts for recognition. This approach assumes that a test sample can be represented by using the features of its true class but requires multiple images of the same person for training purpose. It has a much higher rank 1 accuracy than any of the conventional face recognition methods going as up to 80%. It also shows that the fusion based approach of using vectors from all facial parts bolsters the accuracy double than what it would have achieved without fusing the data.

Bhatt et.al[48] proposed a multi-objective evolutionary algorithm that takes into account the Extended UCLBP[49] features, which preserves the information between neighboring pixels and encodes gray scale information about a neighborhood, and Scale Invariant SIFT[50] features which is a rotation invariant feature extractor preserving magnitude and orientation around interest points. Both these feature extractors are applied on granules obtained from the images. The features obtained are combined using a Genetic algorithm which selects the optimal feature extractor for a particular granule and assigns a proper weight to that particular granule. The weighted χ^2 distance measure is used for recognition purpose. It has a very high recognition rate for a plastic surgery database with rates near about 90% with an even more impressive score on a heterogeneous database which comprise other non-surgical images added to the plastic surgery database. The rank-1 accuracy scores over 90% in the second case. Overall, this method outperforms both EUCLBP, SIFT and their combination with PCA. It also outperforms the sum rule fusion based method[51] which achieves around a 85% identification accuracy on both the databases. Also within the domain of plastic surgery Otoplasty images has a the highest accuracy rate followed by blepharoplasty images with over 90% accuracy while the lowest is Rhytidectomy images possessing just over 70% accuracy.

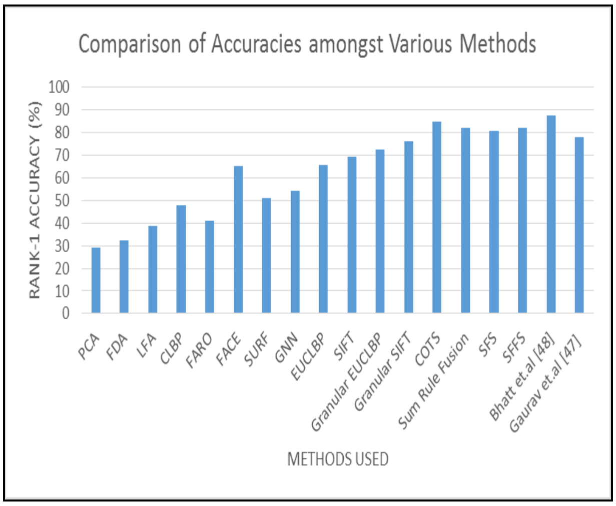

Fig. 3. Accuracy comparison on Plastic Surgery Database[57]

If one compares the various methods discussed one will find that local based feature methods produce better results than methods which relies upon just holistic features. Higher recognition rates are also observed in the methods employing fusion based algorithms. Since the correlation amongst the holistic response and local response is so minimal, fusion based methods will be the way to go forward and it has been proved that they generally produce far superior results when compared to methods employing a certain set of features. It has been also been that approaches which are evolutionary in nature fare better than traditional statistical approaches.

The problems like illumination variation and pose variation escalate the challenge of Plastic Surgery and thus it is often necessary to combine illumination resistant and pose invariant features to obtain better accuracy. Research on Plastic Surgery is fairly new and as no scientific study is conducted on relationships amongst post-surgical and pre-surgical images, new methods in this field is fairly rare thus opening up a lot of potential for future work. A basic comparison of the rank-1 accuracies of various methods on the Plastic Surgery Database is given in Fig. 3.

II. DATABASE CONSTRUCTION

Databases in the field on Human Face Recognition is prevalent everywhere. Popular databases like FERET[55], CMU-PIE[54], AR Face Database[56], etc. are used in almost most facial recognition algorithms. They present a lot of challenges including pose, occlusion, illumination variation and expression changes. It also has various challenges combined with each other. However none of the databases deal with the challenge of plastic surgery primarily because plastic surgery is a very private aspect of life that people do not want to share with others. Therefore it is incredibly hard to find one.

Singh et.al has conducted his experiments on the publicly available database.[57] This database has 1800 pre-surgery and post-surgery images of 900 different subjects. The images have neutral expression, frontal pose and proper illumination. It has 381 individuals who have undergone global plastic surgery with each individual having 2 images. There are 618 images of Rhytidectomy and 146 images of skin resurfacing. Overall there are 519 individuals when it comes to local plastic surgery with each individual possessing 2 images. There are 148 Otoplasty images, 210 Blepharoplasty images and 384 Rhinoplasty images. All the rest are other local surgical images. One image of an individual is taken pre-surgery and the other image is taken post-surgery. Gaurav et.al[45] also used a subset of Multi Biometric Grand Challenge Database (MBGC)[58] with frontal poses, for characterization of facial parts during the training phase.

Building up resources is one of the most important aspect in research and there lies an enormous potential when it comes to develop a database for Plastic Surgery problems relating to human face recognition.

4. CONCLUSION AND FUTURE WORK

This paper shows the different classifications of plastic surgery and various processes that are conducted in this area. Furthermore the paper dwells on the research approaches when it comes to plastic surgery problems and the various categories the methods can be classified into. It discusses the difference between holistic approaches and local region based approaches and the way fusion based methods can take the best elements of both features as holistic response and local region based response has very little correlation amongst themselves. It also explores the aspect of database creation and the challenges associated with it. It is an extremely new field and minimal research has been conducted on both the forming of the algorithms and on the creation of databases. Therefore enormous potential lies in both these areas. Evolutionary algorithms fare well in this application and with the advent of machine learning, more and more methods can be formed based on that approach. Also more fusion based approaches can be established in order to tackle the problem. Also further studies conducted on establishing relationship between pre-surgical and post-surgical images can reveal characteristics that might be worked upon. So it is an open area of research that the future researches need to tackle.

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