FEATURE BASED SURGICALLY ALTERED FACE RECOGNITION SYSTEM BASED ON BIORTHOGONAL WAVELET TRANSFORM

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Abstract
Face recognition system places an important role in many person authentication applications. While recognition of these faces so many problems are there, example pose, illumination, and aging. So many algorithms have been proposed to solve these problems. Now a day's surgically altered face recognition place a major problem in many person identification systems because, plastic surgery is enhance the appearance of the face. Relating of images former and later the plastic surgery process is the crucial task for automatic face recognition systems. This paper propose a novel approach to relate before and after surgery face images. For this extracting the features by using multi biorthogonal wavelet transform in both before and after plastic surgery face images. Match these features by using correlation window. The proposed method takes less time and gives high identification accuracy for face recognition as compared to the existing methods.

Keywords: **face recognition, plastic surgery, biorthogonal wavelet transform.**

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I.INTRODUCTION

Face is an important feature in human body as it provides information such as identifying a person, gender classification, age estimation of a person. However, even after few decades of research, face recognition technology still an active topic because of the variability observed in face recognition due to illumination, pose, etc. now a day's plastic surgery is a new challenge in face recognition systems, because these surgeries enhance the appearance of face and introducing nonlinear components in face image. So it is very difficult to identify the faces before and after surgery [1], [2] .The number of people undergoing these plastic surgeries is increasing every day. The reason behind this transition is due to the intension among people to look young, improved technology with very less in cur period and the cost involved. Figure 1 shows the typical changes in facial features after plastic surgery.

In general, plastic surgery can be classified into two distinct categories.

A) Local surgery [3]: This is a kind of surgery in which an individual undergoes local plastic surgery for correcting defects, anomalies, or improving skin texture. This local surgery is used for correcting jaw and teeth structure, nose structure, chin, forehead and eyelids etc. Local plastic surgery is also aimed at reshaping and restructuring facial features to improve the aesthetics.

B) Global surgery [3]: Global plastic surgery is primarily aimed at reconstructing the features to cure some functional damage rather than to improve the aesthetics. In this type of surgery, the appearance, texture and facial features of an individual are reconstructed to resemble normal human face but are usually not the same as the original

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:

1.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.

2.After surgery, the geometric relationship between facial features changes and there is no technique to detect and measure such type of alterations.

Fig. 1. Illustrating the variations in facial appearance caused due to plastic surgery (images taken from internet).

The main aim of this paper is to add a new dimension to face recognition by discussing this challenge and systematically evaluating the performance of existing face recognition algorithms on a database that contains face images before and after surgery.

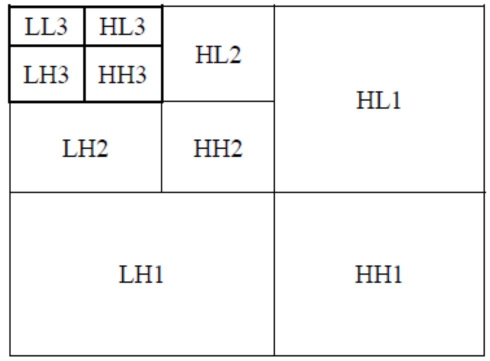
Most of the existing face recognition algorithms have predominantly focused on mitigating the effects of pose, illumination and expression, and no attempt has been made to study the effect of local and global plastic surgery on face recognition. According to R.Singh et al. [4] experimented with already existing algorithms like PCA, LDA, GF, LFA, and GNN and so on. Even these algorithms are getting good results in face recognition approach but these are not able to produce satisfiable result effectively due to alterations in texture representation. Thus there are further more research is need to assuage recognition rate. Raghvendra et al.[5] performed approach of face and ocular regions at aggregate level fusion to increase the recognition rate. SIFT and LBP algorithms are used for feature extraction from ocular region and that global surgery may meeting more than local surgery face recognition and estimated also it generate good accuracy rate from the R.Singh et al. [4]. Gaurav Aggraval et al. [6] introduced sparse representation on local facial mutilation to match surgical face and part wise sparse representation approach. Both approaches extremely out performs and reported better performance with Principle component analysis based representation where minimum error is calculated, if minimum error is calculated then process is success otherwise not. H.S.Bhatt et al. [7] calculated multi-objective approach with granular level approach to relate the former and later surgical face. Firstly produce granules levels of the face images to optimize the selection of feature extractor for each face granules along with weight and reacquired feature with scale invariant feature extraction method. Investigated that propose approach generated good result from the other existing method. Kshitij et al [8] proposed a method to match former and later both images using segmentation into altered granules levels and features are extracted using scale invariant feature transform and Local binary pattern method to acquire different – different information from the face granules. This technique is similar to the H.S.Bhatt [7]. But feature selection is exhibiting with SWARN optimization algorithm. Later this experiment reported that given technique has high degree of recognition accuracy.

II WAVELET BASED FEATURE EXTRACTION

Edge detection is vital task in feature extraction. An edge in an image is a contour across which the brightness of the image transitions precisely. Actually an edge detector is a high-pass filter that can be applied to derive the edge points in an image. Along with edges, the corners are also considered the best features that can be derived from an image. Apart from corners and edges, blobs are also the best applicants for deriving the conspicuous features in an image. Blobs are nothing but regions in the image that may consist of objects of interest and are either darker or brighter than its surroundings. Some of the techniques engaged to identify the blobs are Difference of Gaussian, Laplacian of Gaussian, and Determinant of Hessian etc. which are chosen consequently for the desired application. Harris corner detector [9] is a eminent feature point detector due to its lighting changes and invariance to rotation. But it does not scale-invariant. Lowe in [10] [11], has approached the problem of affine invariance for feature extraction and proposed the so called scale-invariant feature transform (SIFT) descriptor, that is consistent to image rotations and translations to scale changes (blur), and well-conditioned to illumination variations, but it has slow execution time.

The major reason and benefit for applying the wavelet transform to the detection of edges in an image is the feasibility of choosing the size of the particulars that will be detected. Number of edges that we want to acquire is confirmed by the wavelet scale. In discrete wavelet transform, the choice of the scale is achieved by multiple signal passage through the wavelet filter. The wavelet analysis is performed separately for the horizontal and the vertical directions when processing a 2-D image. Thus, the horizontal and vertical the edges are detected separately.

The two dimensional discrete wavelet transform (DWT) separates the images into sub-images, 3 details and 1 approximation. The approximation looks analogous to the input image but only one fourth of the original size. The Two dimensional DWT is an extension of the one dimensional DWT in both the horizontal and the vertical direction. We characterize the resulting sub-images from an octave (a single iteration of the DWT) as LL (the approximation or we say the smoothing image of the original image which consist of the more information of the original image), LH (preserves the horizontal edge features), HL (preserves the vertical edge features), and HH (preserves the diagonal features which are influenced by noise greatly), according to the filters used to produce the sub-image. For example, HL means that we used a high pass filter along the rows, and a low pass filter along the columns. This process can repeat perceptibly by putting the first octave's LL sub-image through another set of low pass and high pass filters. These iterative procedures constitute the multi-resolution analysis. The diagram is shown in Fig 2



III BIORTHOGONAL WAVELET TRANSFORM BASED FEATURE EXTRACTION

It is well known that bases that span a space do not have to be orthogonal. In order to achieve greater adaptability in the construction of wavelet bases, the orthogonality condition is relaxed allowing semi-orthogonal, biorthogonal or non-orthogonal wavelet bases [12]. Biorthogonal Wavelets are families of compactly supported symmetric wavelets. The symmetry of the filter coefficients is often desirable since it results in linear phase of the transfer function [12][13]. In the biorthogonal case, rather than having one scaling and wavelet function, there are two scaling functions that may generate different multiresolution analysis, and accordingly two different wavelet functions. The dual scaling and wavelet functions have the following properties:

1. They are zero outside of a segment.
2. The calculation algorithms are maintained, and thus very simple.
3. The associated filters are symmetrical.
4. The functions used in the calculations are easier to build numerically than those used in the Daubechies wavelets [14]

From a practical point of view, signal processing always has to deal with the quantization problem. As long as we stay in a L^2 setting, any Orthonormal basis allows a signal to be reconstructed exactly. In practice, however, the coefficients of signal decomposition must be quantized. Such approximations arise from limited machinery accuracy or are imposed by a desire to compress the data. If we use a discontinuous wavelet, such as the Haar wavelet, it happens that spurious edges appear and the visual effects can be annoying.

Although the uses of smooth orthogonal wavelets produce better results, they have not completely satisfied the experts in image processing. One reason is the lack of symmetry. The scaling function φ should be even, i.e., $\varphi(x) = \varphi(-x)$, and the wavelet ψ should be symmetric around x = $x = \frac{1}{2}$, i.e.,

$$\psi(1-x) = \psi(x) \quad (1)$$

A lack of this symmetry in combination with quantization leads to visible defects. The reason is that quantization errors usually are most prominent around edges in images, and our visual system seems to be more tolerant of symmetric errors than of asymmetric ones. Moreover, symmetric filters make it easier to deal with the boundaries of an image. Symmetric filters are also called "linear phase filters" by engineers, which more precisely means that the function $h(y) = \sum_k h_k e^{-iky}$ of a filter with filter coefficients h_k satisfies $h(y) = e^{-i/y}|h(y)|$ for some half-integer l, which is equivalent $h_k = h_{2l-k}$ Although certain orthogonal wavelets in fact are symmetric, they do not hold for wavelets with compact support. However, giving up the condition of orthogonality, we gain a degree of freedom which enables us to incorporate the desired symmetries together with continuity and compact support property.

There are several ways to construct two-dimensional wavelets from given one-dimensional ones. One possibility is simply taking the tensor product of two one-dimensional wavelet basis as 2-basis, e.g., $\Psi_{jkj'k'}(x,y) = \psi_{jk}(x)\psi_{j'k'}(y)$. the resulting functions are indeed wavelets, and $(\Psi_j)_{j\in z^2}$ is a Riesz or Orthonormal basis of $L^2(R^2)$. If ψ_{jk} is a Riesz or orthonormal basis of L(R), respectively. In this basis, the two variables x and y are dilated and translated separately. For many applications, however, there is a more appropriate construction in which the dilations of the wavelet basis control both variables simultaneously. Here it is not the tensor products of wavelets which we start from, but the one-dimensional Multiresolution analysis $V_j \subset V_{j+1}, j \in Z$ we define inductively,

$$V_0 = V_0 \otimes V_0 \quad (2)$$

$$f(x,y) \in V_j \Leftrightarrow f(2^j x, 2^j y) = V_0 \quad (3)$$

Where

$$V_0 \otimes V_0 = casure(span\{f(x,y) = f_1(x) f_2(y) : f_1, f_2 \in V_0\})$$

, i.e. $V_0 \otimes V_0$ denotes the tensor product of vector spaces. Then the Vj form a multi resolution ladder…, $V_{-1} \subset V_0 \subset V_1 \subset V_2$ …… in $L^2(R^2)$. Since $\varphi(x-k)$ form a riesz basis for V_0, the product functions

$$\Phi_{j,k}(x,y) = 2^{-j}\varphi(2^{-j}x - k_1)\varphi(2^{-j}y - k_2),$$

$$k = (k_1, k_2) \in z^2, \quad (4)$$

Form a riesz basis for V_j. As in one-dimensional case, we define each W_j, for $j \in Z$, as the orthogonal complement of V_j in V_{j-1}, such that $V_{j-1} = V_j \otimes W_j$. An interesting observation is made if we compare this decomposition with the algebraic properties of the spaces given by construction,

$$V_{j-1} = V_{j-1} \otimes V_{j-1} = (V_j \oplus W_j) \otimes (V_j \oplus W_j)$$
$$= (V_j \otimes V_j) \oplus (W_j \otimes V_j) \oplus (V_j \otimes W_j) \oplus (W_j \otimes W_j)$$

Thus W_j consists of three orthogonal subspaces with Riesz bases given by $\psi_{j,k_1}(x)\varphi_{j,k_2}(y)$ for $W_j \otimes V_j$, $\varphi_{j,k_1}(x)\psi_{j,k_2}(y)$ for $V_j \otimes W_j$, and $\psi_{j,k_1}(x)\psi_{j.k_2}(y)$ for $W_j \otimes W_j$. This leads us to define three wavelets, $\Psi^h(x,y) = \varphi(x)\psi(y)$, $\Psi^v(x,y) = \psi(x)\varphi(y)$, $\Psi^d(x,y) = \psi(x)\psi(y)$, where h, v, d stands for "horizontal", "vertical", and "diagonal", respectively. Then, for $j \in Z$ given, $\{\Psi^h_{j,k}, \Psi^v_{j,k}, \Psi^d_{j,k} : k \in Z^2\}$ forms a basis of W_j, whereas $\{\Psi^h_{j,k}, \Psi^v_{j,k}, \Psi^d_{j,k} : k \in Z^2\}_{j\in Z}$ forms a basis of $L^2(R^2) = \oplus_j W_j$ Then the dual scaling function is $\tilde{\Phi}(x,y) = \tilde{\varphi}(x)\tilde{\varphi}(y)$ and the dual wavelets are

$$\tilde{\psi}^h(x,y) = \tilde{\psi}(x)\tilde{\varphi}(y), \tilde{\Psi}^v(x,y) = \tilde{\psi}(x)\tilde{\varphi}(y), \tilde{\Psi}^d(x,y) = \tilde{\psi}(x)\tilde{\psi}(y)$$

IV. ALGORITHM FOR PROPOSED METHOD

A.**Feature extraction using biorthogonal wavelet transform:**

If an image is partitioned by the biorthogonal wavelet transform then four sub images can be achieved. One is real part of low-detailed sub-image can be achieved from the low frequency component LL (x, y). Second and third are the combinations of real and imaginary part of detailed sub-images can be obtained from the high frequency components LH(x, y) & HL(x, y). Fourth one is the imaginary part of the detailed sub image can be achieved from high frequency component HH (x, y). In the second level decomposition we partitioned the high frequency components because a feature is a robust point in the image i.e. a high frequency component. In this paper, we partitioned the image up to second level only and each level; we combine all high frequency components and leave the low frequency components in each level.

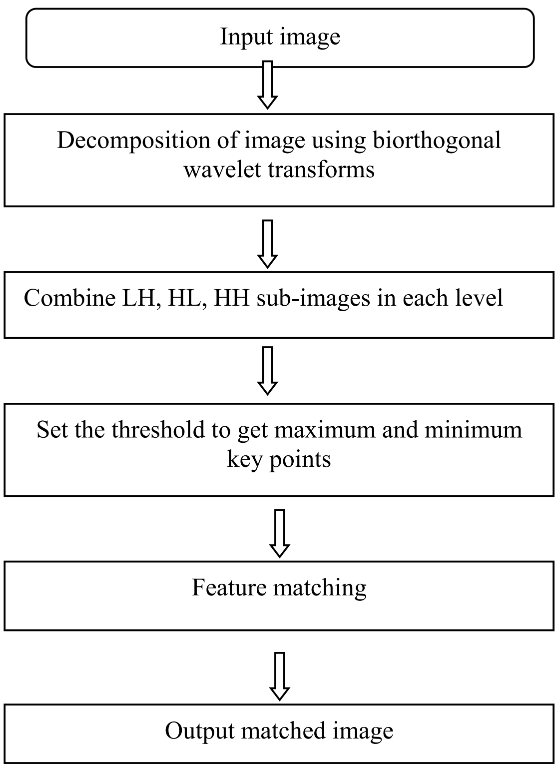


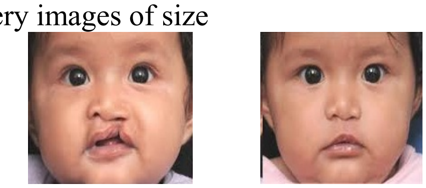
Fig. 3. Block diagram of the proposed method

B. Feature matching

Feature matching aims to detect the related features from the both images. In this paper, correlation method is used to calculate allied features between two images. In this techniques analyze pixels around each point in the first image and correlate them with the pixels around every other point in a second image. The most colloquial points are taken as matching pairs. It can be seen very well from the picture, however, that many points have been wrongly correlated. To overcome this drawback we use Homography Estimation is used. It can be used to project one of the two images on top of the other while matching the majority of the correlated feature points we constrained a Homography matrix, which has the opportunity to relate the two images. First detect the correct key points by using RANSAC. It is the algorithm to estimate the mathematical model of a set of observed data. Observed data contain both inliers and outliers. Where inliers correspond to a set of data that can be described by some set of parameters, whereas outlets cannot be described by a model. So, for an accurate model fitting, these outlets have to be eliminated.

Algorithm for proposed method:

Step-1: Take former and later face plastic surgery images of size



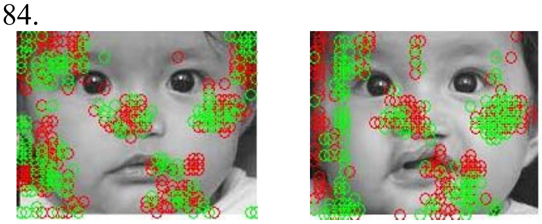
Step-2: Partitioned the two input images by using biorthogonal wavelet transform up to the second level only. Here we are using bior 6.8 wavelet.

Step3: Combine LH, HL, HH sub-images in each level

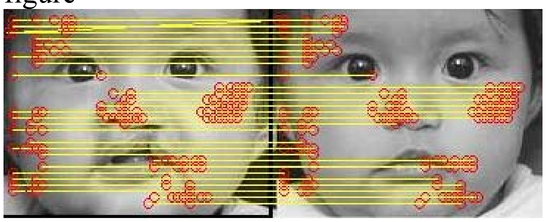
Step4: Set the threshold to get the maximum and minimum number of key points.

Step5: Project these points in an image by multiplying four times of each key point location because of the second level of biorthogonal wavelet decomposition the image can be analysis done on one fourth part of the original image.

Step 6: Plot the maxima and minima key points which are obtained from the threshold. The red color circle indicates the maximum key point in the image and green color circle indicates the minimum key point in the image. Here total number of key points detected in both images is 1384.



Step 7: After obtaining the key points in both the images the next step is identifying the matching points in both images for this process first fit the key points by using RANSAC and match these key points by using correlation and homography matrix. The output matched image as shown in figure



V.CONCLUSION

Plastic surgery face detection is a major problem in many biometric identification systems. In this paper a new method based on biorthogonal wavelet transform we extract invariant features in before and after plastic surgery face images. In this each level we combine all detailed coefficients because the feature is the strong point it also presents in horizontal, vertical and diagonal regions. Compare with the other methods biorthogonal wavelet transform gives strong features with less number of coefficients. The experimental images taken form internet show that high recognition rate obtained by the proposed method compare with other methods.

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