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## Automatic Frontal Face Reconstruction Approach for Pose Invariant Face Recognition

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### Abstract

Handling pose variations for face recognition system is a challenging task. The recognition rate is drastically decreasing with the images captured in uncontrolled environment having pose variations in yaw, pitch and roll angles. When the face image with frontal pose it is proved that the recognition system performs well. In this research an attempt is made to reconstruct frontal pose face images from non-frontal face images to improve the face recognition accuracy. By estimating the change in pose with respect to yaw, pitch and roll angles based on the landmark points best viewed side of the pose is identified. Using tilting, stretching and mirroring operation to the best viewed side, frontal pose is obtained. This approach is database independent, training free and no need to generate 3D model and not using any fitting approach, which is a complex task and handle any combination of roll, yaw, pitch angle up to  $\pm 22.5$  degrees only from the 2D landmark points. Experiments were conducted on FERET, HP, LFW, PUB-FIG data bases and the experimental result proves that our approach can handle the uncontrolled faces with arbitrary poses. Experimental results on various controlled and uncontrolled poses proved the effectiveness of the proposed method.

Keywords: Face Recognition, Uncontrolled, Frontal, Non-Frontal, Landmark Points, Best Viewed, Tilting, Stretching, Mirroring, Reconstruction.

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### 1. Introduction

Real World Face Recognition in an uncontrolled settings is the most challenge research topic in the past few years with enormous applications viz. surveillance, crime investigation, boarder control, military applications etc., handling pose variations between the probe and the gallery images acquired in the uncontrolled environment is still remains a challenge and needs lot of attention since the performance drops for such non-frontal images with large pose variations. Most of the face recognition algorithms yield satisfactory performance for the frontal faces. However matching the non-frontal faces directly is a difficult task. One intuitive solution is to reconstruct the frontal face from the non-frontal face for further processing. The pose invariant face recognition algorithms are mainly categorized into three categories such as invariant feature extraction based methods, multi-view based methods, pose normalization based methods [1-11]. The ultimate idea of pose normalization is by generating a novel pose of either the probe image as similar to that of the gallery image or by the reverse based on the 3D model. The other idea of pose normalization is by synthesizing the frontal view of gallery and probe image which is otherwise known as frontal face reconstruction.

Only a very few works explored the idea of frontal face reconstruction [10-11] to improve the accuracy of face recognition. The existing methods suffer from any of the drawbacks such as not fully automatic, not allow the combined pose variations, database specific, need lot of training, uses 3D model generation, uses huge landmark points methods and manual selection of required points, using fitting approaches etc, Chai et al [1]. Learn pose-specific locally linear mappings from patches of non-frontal faces to patches of frontal faces. Their method only handles a discrete set of poses and requires some manual labeling of facial landmarks. Similarly in the approach of Asthana et al [4] several non-frontal synthetic images are generated from frontal gallery images and this method has the limitation for discrete set of poses and required landmark point are manually selected. Gao et al. [8] use a single Active Appearance Model (AAM) to fit non-frontal faces but also require manual labeling. Du and Ward [3]. require a set of prototype non-frontal face images that are in the same pose as the input non-frontal face. Heo and Savvides [9]. use a similar approach to ours for locating facial feature points but use 2D affine warps instead of our more accurate 3D warps and rely on manual initialization. Blanz and Vetter [5] use a 3D Morphable Model to fit a non-frontal face image and then synthesize a frontal view of the face and uses manual marking of several facial feature points. Huy Tho Ho [10]. present a

method for reconstructing virtual frontal face from non-frontal face using MRFs and BP algorithms. A lot of training is needed for aligning the input non-frontal face with that of the frontal faces available in the training database and it is not fully automatic. Maria De Marsico [11]. uses the Extended Active Shape Model called STASM algorithm for landmark point detection. out of 68 landmark points of STASM the points needed for frontal face reconstruction are selected manually. Since very long back itself it is proven that the face recognition accuracy is good for the frontal faces. However in the real time scenario the face images captured is not always frontal and has arbitrary pose variations comprising all possible directions. Hence it is a high demand for the face recognition methods that can able to handle such faces and it is proposed to reconstruct a frontal face from the non-frontal face to improve the recognition accuracy using very few 2D landmark points.

## 2. Proposed Approach

A novel approach is proposed for frontal face reconstruction from non-frontal faces captured in controlled, uncontrolled settings. The proposed Frontal face reconstruction method is capable of reconstructing a frontal face image from a single non-frontal image, fully automatic and the YPR 3-axis pose coverage of the uncontrolled faces without applying any 3D techniques and training methods.

The entire framework for frontal face reconstruction is shown in Fig. 1. In the first stage the landmark points are detected and in the subsequent stages better viewed half selection, approximation of other half based on the better half are discussed.

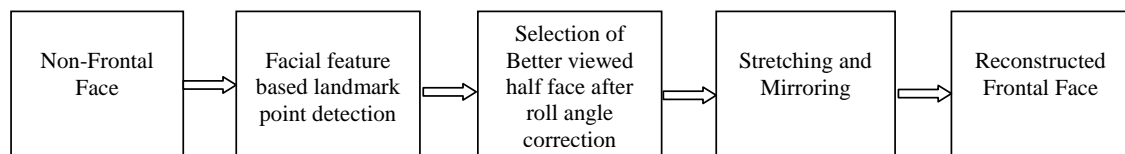


Fig. 1 Framework for Frontal Face Reconstruction

The process of reconstructing frontal face from non frontal face is depicted in Fig. 2, the frontal face reconstruction via TSM algorithm. From the non-frontal face by estimating the roll angle and from the salient landmark points the frontal face is reconstructed with stretching and mirroring operations. The facial components such as left eye, right eye, nose and mouth are detected using the object detection algorithm [12, 13]. The landmark points and subsequent division of face image into two halves depends on the quality of object detection process. Given a test image, our approach automatically detects the face and facial features such as eye(s), nose, mouth that will be the initial step for the landmark point detection. If no face or if both the eye features are not detected, a failure to acquire has occurred and for such images frontal face reconstruction is not possible. For all other images facial feature based landmark points can be detected and by using these points frontal face is reconstructed from the given non-frontal face. Similarly for the uncontrolled face images with occlusion in the eyes such as front hair covering eyes, sunglasses, closed eyes, large pose variations, high illumination, low resolution etc., the face or facial feature detection fails. In case of facial feature detection fails landmark point detection also fails since it relies completely on detection of facial features such as left eye, right eye, nose, mouth.

It has a advantage that, it does not require training process, head pose estimation, 3D model generation, landmark point fitting, manual selection of landmark points, necessity of frontal face availability in the gallery etc., In the case of face images has pose variations in the left direction from the viewer perspective, the some of the facial features are not detected correctly and hence accurate landmark point detection fails. However for the same image if we use the annotated landmark points then our proposed Frontal face reconstruction works promptly.

The rest of the paper is organized as given. Section 2 presents automatic landmark point detection, better viewed half selection, other half approximation based on the better half. Section 3 shows the results. Section 4 ends up with conclusion.

### 1.1. Automatic Landmark Point Detection Based on Facial Features

In order to attain the full automation, the proposed approach uses a novel method to detect the landmark points. The Viola Jones Cascade Object Detector using Haar features and Adaboost cascade classifiers [12-13] is used to detect the facial components such as left eye, right eye, nose, mouth. Based on the facial features four landmark points such as left eye center point, right eye center point, nose tip point, mouth point are detected by the finding the midpoint of the eye(s), nose, mouth rectangular features and the two other landmark points are derived from the mentioned four points. such as midpoint of the two eye centers, chin point. The chin point is derived from the nose tip and mouth point by placing a landmark below the mouth point with the distance of nose tip and mouth point as illustrated in fig. 3.

Given a non-frontal image  $x$ , for with the frontal face is to be reconstructed  
 Procedure:

1. I/P : Non Frontal Image
2. Face ROI detection
3. Facial Component detection : Left Eye , Right Eye, Nose, Mouth
4. Facial component based and derived landmark point detection
5. Compute  $\theta$  between the line connecting two eye centers and the  $x$  axis.
6. If  $\theta > 0$  tilt image in the clockwise direction up to the  $\theta$  value  
 $\theta < 0$  tilt image in the counter clockwise direction.
7. Divide the detected face into two halves such as left and right by connecting the landmark points vertically located on the face.
8. Compute  $d_{nl}, d_{nr}$   
 $d_{nl}$  : The distance between left eye center point, nose point.  
 $d_{nr}$  : The distance between right eye center point, nose point.
9. If  $d_{nl} > d_{nr}$  the better half is the left of the face otherwise right half.
10. Extend / Stretch better half face with respect to the center line of the face ROI.
11. Apply mirroring operation to the stretched better half to get mirrored half
12. O/P : Reconstructed frontal face

Fig. 2 - Frontal Face Reconstruction via TSM

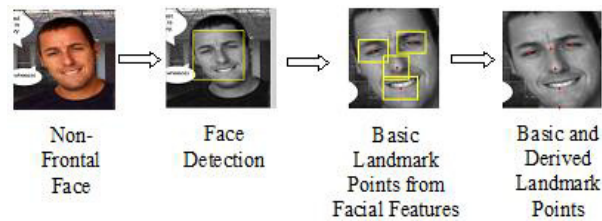


Fig. 3. Landmark Point Detection

### 1.2. Tilting Stretching Mirroring for Frontal Face Reconstruction

For a given image, the facial feature based landmark points are detected automatically to initialize the better half detection process. Where the basic idea is the approach used in [11], unlike in the existing methods which uses many number of landmark points, our proposed approach uses only six landmark points for the entire better half detection and other half approximation. The two eye center points are used to correct the head roll angle if any for the given non-frontal image by tilting the image to an angle  $\theta$ , either in the clockwise or anticlockwise direction around its center point based on the value of  $\theta$  using nearest neighbor interpolation up to the image becomes null angle error in roll (z axis) distortion. If the given image does not possess roll angle distortion then head roll correction process is not required.

After rotating the face ROI to an angle  $\theta$ , a line is drawn by connecting the four landmark points such as midpoint of the two eye centers, nose tip point, mouth center point, chin point and the drawn line is extended in the upward direction to make the face image into two halves such as left half and right half. Then the entire face ROI boundary is splitted into two equal regions.

By measuring the distance between nose tip and the eye center points represented as  $d_{nl}$  and  $d_{nr}$  as shown in the equation, based on which better visible half of the face image is identified. If  $d_{nl}$  is equal to  $d_{nr}$ , the given image is a frontal face, hence it is assumed that no need for Frontal Face Reconstruction.

$$d_{nl} = \sqrt{(no_x - le_x)^2 + (no_y - le_y)^2}$$

$$d_{nr} = \sqrt{(no_x - re_x)^2 + (no_y - re_y)^2}$$

where  $(no_x, no_y)$  is the pixel value of nose tip point and  $(le_x, le_y), (re_x, re_y)$  are the pixel value of left eye center, right eye center respectively.

If  $(d_{nr} > d_{nl})$ , it is assumed that the better visible half of the face is right half and hence it is decided to consider the right half as reference for the reconstruction process and the other half face pixels are filled with "0" value. The virtual line is drawn for

dividing the face ROI into two regions such as left region and right region. The decided better half in the respective region will not be straight and hence the for an efficient reconstruction process the better visible half face is to be made straight and hence stretching is to be followed, since some pixels of the visible half face may be overlapped in the other half or some pixels may be missed in the considered better half of the face. Hence the overlapped portion has to be stretched from the other half face to the better visible half or missed portion has to be stretched from the considered better visible part of the face. Stretching is the process by which the missing pixel values are filled with the values of the existing previous pixel values, overlapped pixel values are replaced with the existing pixel values in the better exposed part of the face. A stretching operation is applied to all of the rows of the better exposed tilted half face to make them of constant length and without missing any pixel values for the subsequent reconstruction process.

After successful stretching, the mirroring operation is applied for frontal face reconstruction. Here mirroring also called flipping or reversing an image across horizontal axis. For horizontal flipping  $[x=x*-1, y=y]$  is used for matrix transformation. The face ROI of size  $A \times A$  is divided into two equal halves of size  $A/2 \times A/2$ . The pixel values in the better exposed half region of the matrix of size  $A/2 \times A/2$  is flipped with its columns in the left-right direction. where  $A$  is a symmetrical matrix and hence  $A/2$  is also a symmetrical matrix.

By combining the better exposed tilted, stretched half face matrix and the mirrored half face matrix the reconstructed frontal face is obtained. The better exposed half face image after the following process of tilting, stretching, mirroring will be in frontal face.

### 3. Results and Discussion

We conducted frontal face reconstruction experiments on the FERET [14], HP [15], and LFW [16], PUB-FIG [17] databases. The FERET and HP databases are the most commonly used databases for face recognition across pose variations under controlled settings and LFW and PUB-FIG databases are for the uncontrolled settings. The face images in the FERET, HP databases are captured in the controlled environment. FERET deals with only yaw pose variations and HP deals with both yaw and pitch variations. Pose variations with respect to horizontal axis, horizontal and vertical axis respectively. The LFW and PUB-FIG database face images are captured in the uncontrolled scenario and has yaw, pitch, roll pose variations either individually or in combinations along with variations in other factors such as illumination, expression, resolution, make up variations, age variations, partial occlusion etc. However the proposed algorithm for frontal face reconstruction is database independent. The experiments on LFW and PUB-FIG highlight the ability of our system to handle combined pose variations in the yaw, pitch, roll angles accurately. Fig 4. shows the frontal face reconstruction results for the various persons and Fig. 5 shows the frontal face reconstruction of the same person with different poses of FERET, HP, LFW, PUB-FIG databases. The result shows the reconstructed frontal view of the non-frontal faces.

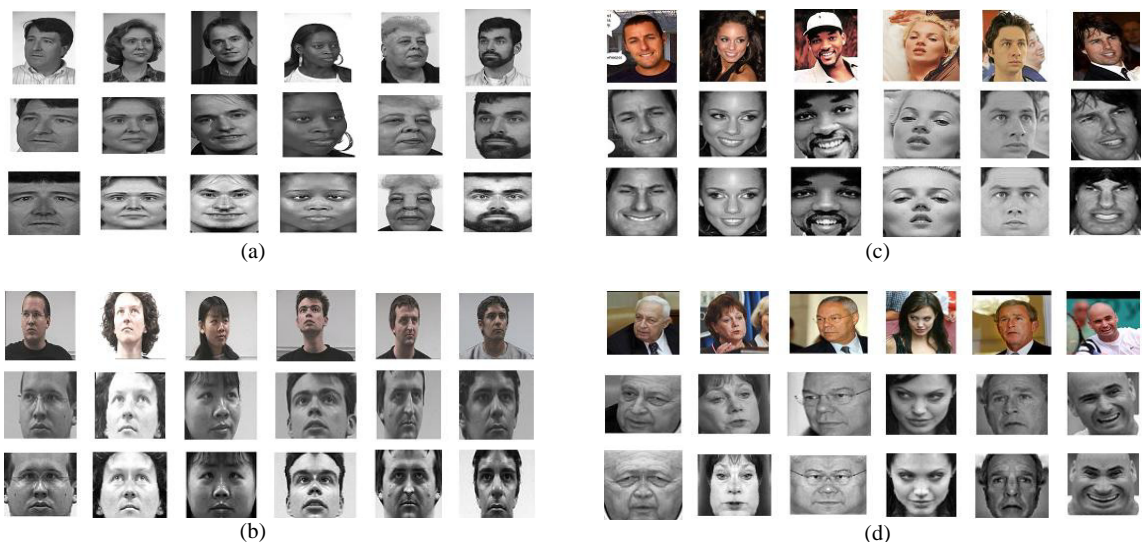


Fig. 4. Results of Frontal Face Reconstruction from (a) FERET, (b) HP, (c) PUB-FIG, and (d) LFW of different persons with pose variations. In each, Top row contains the non-frontal input images, middle row contains the detected face and the bottom row contains corresponding reconstructed frontal face images



Fig. 5. Results of Frontal Face Reconstruction from (a) FERET, (b) HP, (c) PUB-FIG, and (d) LFW of same person with different pose. In each, Top row contains the non-frontal input images and the bottom row contains corresponding reconstructed frontal face images

For the frontal faces, there are absolutely no pose distortions in the XYZ axis. The Yaw, Pitch, Roll angle distortions should not exist. In the proposed approach using the parameters  $\theta, d_{nl}, d_{nr}$  we can prove the reconstructed frontal faces possess null roll. Yaw angle distortions. For the frontal faces the value  $\theta$  should be zero and the values  $d_{nl}$  should be equal to  $d_{nr}$ .

Table 1. Illustration of Pose Parameters describing the Frontal View of the Face Image of each four Test Images of FERET, HP, LFW, PUB-FIG DATABASES (a) Non-Frontal faces and (b) Corresponding Reconstructed Frontal Faces

Database / Test Image	Non-Frontal Face Images (a)			Reconstructed Frontal Face Images (b)		
	$\theta$	$d_{nl}$	$d_{nr}$	$\theta$	$d_{nl}$	$d_{nr}$
FERET/Test Image 1	+0.0063	48.1300	32.8824	0.0059	67.7201	67.8620
FERET / Test Image 2	+0.0031	38.8973	43.4195	0.0046	74.9216	74.2243
FERET / Test Image 3	+0.0042	46.0027	37.1248	0.0041	75.3523	75.0733
FERET / Test Image 4	+0.0037	42.1930	43.2001	0.0012	77.1508	77.4301
HP / Test Image 1	+0.0086	33.1059	38.5876	0.0024	56.5189	56.9386
HP / Test Image 2	+0.0012	36.2008	34.6771	0.0009	57.1985	57.0197
HP / Test Image 3	+0.0049	36.2802	36.7922	0.0040	56.1271	56.4243
HP / Test Image 4	+0.0054	37.2022	37.8646	0.00598	57.0110	57.4012
LFW / Test Image 1	2.89114	32.4423	36.2802	0.0091	69.9232	69.5067
LFW / Test Image 2	-2.7778	38.4220	39.3224	-0.0117	73.4932	73.4767
LFW / Test Image 3	2.9960	30.4508	30.7774	0.0069	73.7055	73.8705
LFW / Test Image 4	3.1266	35.7106	29.4109	0.0023	74.3001	74.5207
PUB-FIG / Test Image 1	+3.0061	45.0694	42.4264	0.0059	77.4290	77.9567
PUB-FIG / Test Image 2	+2.9429	43.9602	44.5225	0.0087	83.1460	83.1724
PUB-FIG / Test Image 3	-2.6823	28.5440	33.2415	-0.0073	67.1018	67.9154
PUB-FIG / Test Image 4	-1.1153	44.1192	35.4683	-0.0052	52.3927	51.9949

Table 1. describes the  $\theta, d_{nl}, d_{nr}$  values for the non-frontal faces of four test images of each four datasets such as FERET, HP, LFW, PUB-FIG and the corresponding reconstructed frontal faces in terms of  $\theta, d_{nl}, d_{nr}$  for the same 16 images. Where (a) represents the parameters deciding the roll, yaw pose variations such as  $\theta, d_{nl}, d_{nr}$  for the non-frontal test images of various controlled, uncontrolled databases and (b) represents the same for the reconstructed frontal faces to prove its reconstruction



accuracy. For the test images of controlled databases such as FERET, HEAD POSE databases the  $\theta$  value is negligible since the images does not possess roll angle variations. A FERET image varies only in yaw pose distortion in both the left and right directions. Similarly HP images has yaw and pitch variations in left, right and up, down respectively. It is observed that for the images turns in left direction  $d_{nr}$  value is higher compared to  $d_{nl}$  value however for the images turns in right direction it is reverse.

For the test images of familiar uncontrolled databases LFW, PUB-FIG, the images has arbitrary pose variations including roll, yaw and pitch. The value of the angle  $\theta$  may be either positive or negative and measured using left, right center points. Right eye point is the reference point for correcting the head roll angle. if the "y" coordinate of the right eye center point is less than the "y" coordinate of the left eye center point then the angle  $\theta$  is positive. Similarly for the right eye center point is greater than the "y" coordinate of the left eye center point then the angle  $\theta$  is negative.

## 5. Conclusion

A fully automatic frontal face reconstruction algorithm from the non-frontal faces with is essentially needed for the pose invariant face recognition is proposed. The proposed algorithm designed to address the unsolved problem of reconstructing frontal faces from the faces captured in the uncontrolled scenario with 3-axis pose variations along with the other challenges like illumination, expression, age variations etc. Since it is proved that the face recognition accuracy is good for the frontal faces, our frontal face reconstruction method will significantly improve the recognition. From the results it is proven that from the non-frontal face images the frontal face images are reconstructed more accurately. Since we are concerned about the frontal view of the face, we dealt with the roll and yaw measurements to verify the accuracy of the reconstructed frontal face images. The frontal view of the reconstructed images are better viewed compared to the state of art pose normalization methods exists so far and it is proven that it suits well for the real time applications where pose invariant face recognition is needed for the faces with arbitrary pose variations since training is not needed and no part of the algorithm needs any manual intervention. The proposed approach not needs the traditional ASM, AAM, and its derivatives. In future work, we plan to extend the system to wider range of uncontrolled pose faces and to apply this for face recognition task.

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