

Recognizing Occluded 3d Face Using Block Matching Algorithm and PCA

Riddhi Patel¹ Shruti B. Yagnik²

¹ Department of Computer Engineering ² Department of Information Technology
^{1,2} Gujarat Technological University, Gujarat, India.

Abstract— With improvement in sensor technology 3d face recognition has become an imminent technology due to its non co-operative nature. Many researches in 3d face recognition have been dealing with the problem of pose variation, expression, aging and occlusion. We show that under utmost occlusion due to hair, hands, scarves, hats, glass typical 3d face recognition system exhibit poor performance. This paper presents restoration strategy for effective 3d face recognition. In this paper we propose two algorithms for occlusion detection and face recognition. First the occluded face region is detected by matching blocks with the original face. The non occluded regions are then used to restore the missing information. BMA used to restore occluded face. Then apply PCA for recognition. The experimental results show the higher computational efficiency and robustness to occlusion.

Keywords: 3D face recognition, Block matching Algorithm, Principal Component Analysis, occlusion.

I. INTRODUCTION

The real challenge in bio metric technologies is the ability to handle all those scenarios where subjects are non co-operatives. The face is one of the best candidates among all bio metrics like finger print, Iris, gait, speech. The face is non touch bio metrics and the natural way people use to recognize each other so it is more acceptable by the users. The main factors that affect the accuracy of the face recognition system are illumination and pose variations, facial expressions, aging and occlusion.

Occlusion is one of the main performance reduction problems in face recognition system. There are three types of occlusion mainly: self occlusion, inner object occlusion and background occlusion [1]. When some part of the object is occluded is called self occlusion. When two or more object occluded each other, called inter object occlusion. If the object are hidid due to back ground object in the scene, background occlusion occurs.

The main problem in occlusion detection is that it cannot detect directly. To detect the occlusion, pixels of the occluded regions are detected. Occlusion detection is used for the restoring the occluded part of the image. Accurate occlusion detection and interpretation will help the user to get accurate information.

The strategy, here illustrated, approaches the problem by dividing the face in number of blocks. First the occluded regions are detected and then the non occluded regions are used to restore the image. And after that principal component analysis method is used to recognize the face.

The paper is organized as follow: section 2 describes the related works. Section 3 describes the proposed methodology for face recognition. Section 4 reports the results obtained on a dataset of occluded face.

Section 5 discusses the conclusion and our plan for future work.

II. RELATED WORK

Alessandro Colombo et al. [2] present the strategy for the restoration of occluded 3d face. This strategy working on partially occluded face. In this innovative strategy there are two steps: in first step occlusion is detected and in second step non occluded regions are used to restore missing parts. Holistic and feature based approach are used to restore the missing information. In restoration strategy occlusion is detected from a comparison of the input image with a generic model of face. A general model of faces is provided by the eigenface approach. Face restoration is based on Gappy principal component analysis. This strategy find rare false positives and non occluded face are regularly recognized. The disadvantages of this method are that this method is correctly working on the weak occluded face. Strong occluded face is not correctly recognized. And this method is used for small datasets.

Michael De Smet et al. [3] has presented method for pose and illumination invariant under occlusion from single image. On the basis of appearance of a face in an image this method estimates the parameter for 3d morphable model. Parallel the occluded regions of the face are identified and excluded for further computation. The visibility-map is used to locate and extent of these occlusions by means of latent binary random variable map. The author model the visibility map as a Markov Random Field (MRF) to account the spatial coherence of occluded regions. This results in a Generalized Expectation-Maximization (GEM) algorithm, which alternates between estimation of the visibility map and optimization of the camera, lighting and 3DMM related parameters. The validity of the approach is verified by a face recognition experiment in which we identify people from facial images contaminated by varying degrees of occlusion. This algorithm is verified by a face recognition experiment using images from the publicly available AR Face Database. The disadvantage is for the scarves scenario the result was rather poor because the scarves covers entire lower portion of the face.

Hamdi Dibekliglu et al. [4] present fully automatic 3D facial landmarking algorithm which relies on accurate statistical modeling of facial features. In this paper they develop statistical and heuristic approaches for 3D facial landmarking. The statistical approach is useful for frontal faces to detect different landmarks with a single method. The statistical method used to generalize different acquisition and preprocessing conditions successfully, but not to different expression conditions. The method use for statistical landmark localization is based on an analysis of local features to determine the most likely location for each landmark. The structural information can be integrated after this stage, having more control on the relative contributions

of local features and structural information. For detect the landmarks separately they model the distribution of features sampled from near the landmark locations in the training set. An author uses a mixture of factor analysers (MoFA) as an unsupervised model. A MoFA is same as a mixture of Gaussians, but the parameter space for the covariance matrix is better explored. In the training stage, clustering and dimensionality reduction are performed in “conjunction”. For a training set and a given MoFA model maximum likelihood parameters can be computed with the Expectation-Maximization (EM) algorithm. Here they use an incremental MoFA algorithm which starts with a one-factor, one-component mixture and adds new factors and new components until a stopping condition is satisfied. The statistical method is not successfully coping with pose, occlusion and expressions variance. So they describe a heuristics method to localize nose tip under sever conditions. They proposed algorithm to find discrete candidate regions for the nose, and selects the most plausible location based on curvature values, which is rotation and scale invariant. They validate this algorithm with Bosphorus 3D face database.

Nese Alyuz et al. [5] propose a new 3D face registration and recognition method based on local a facial region which is able to provide better accuracy in the presence of *expression variations* and facial occlusions. The main aim of this approach is to find the regional corresponds between two different faces. . The first main step of the system is the coarse and dense ARM-based registration than the second one is region-based matching and the last step is classifier fusion. They used an Average regional model (ARMs) which is based on Average face mode approach, where local correspondences are inferred by the Iterative Closest Point (ICP) algorithm. The facial area is divided into different components such as eye, mouth, cheek and chin regions. Registration of faces is carried out by separate dense alignments to relative ARMs. The dissimilarities between the gallery and test faces obtained for individual regions are then combined to determine the final dissimilarity score. If the system is designed to focus only on the regions such as the eyes or the nose, it may be possible to obtain sub-optimal identification accuracy when neutral faces are present during identification since cheeks and chin regions may also add to the discriminative power of the classifier. For the occlusion problem they allow their decision making algorithm to automatically detect and reject the information coming from occluded region experts. The results demonstrate on challenging databases which shows that the proposed system improves the performance of the standard ICP-based holistic approach by obtaining 95.87% identification rate in the case of expression variations. When facial occlusions are present an identification rate improves from 47.05% to 94.12%.

Sung jooLee a et at. [6] present another method for 3d face reconstruction multiple 2d face images. It presents the 3d face reconstruction method which is robust to self occlusion. They propose a shape conversion matrix (SCM) which estimates the ground-truth 2D facial feature points (FFPs) from the observed 2DFFPs corrupted by self-occlusion errors. . To make the SCM, the training observed 2DFFPs and ground-truth 2DFFPs are collected by using 3D

face scanners. An observed shape model and a ground-truth shape model are then used to represent the observed 2DFFPs and the ground-truth 2DFFPs, respectively. Finally, the observed shape model parameter is converted to the ground truth shape model parameter via the SCM. By using the SCM, the true locations of the self-occluded FFPs are estimated exactly with simple matrix multiplications. The combination of SFM-based 3D face reconstruction methods with the proposed SCM become more robust against point correspondence errors caused by self-occlusion, and the computational cost is significantly reduced and also give higher accuracy and faster processing time than the method used without SCM. The advantage of this proposed method is that it does not require an occlusion detection method to find the visible FFPs because the expected locations of the self- occluded FFPs are estimated from all the observed FFPs by using the SCM.

Nese Alyuz et. al [7] presents Facial occlusions pose significant problems for automatic face recognition systems. Under extreme occlusions due to hair, hands, and eyeglasses, typical 3D face recognition systems exhibit poor performance. In order to deal with occlusions, the proposed system employs occlusion-resistant registration, occlusion detection, and regional classifiers. In this work, they aim to tackle the occlusion handling problem by i) designing an occlusion invariant 3D facial registration method, ii) detecting the occluded areas to obtain occlusion-free surfaces, iii) restoring or ignoring the missing parts, and iv) using multiple regional classifiers. In this work, they handle registration by a nose-based approach which assumes partial visibility of the nose. After automatically locating the nose area, a local rigid surface fitting with the Iterative Closest Point (ICP) method is carried out. Once faces are transformed into a canonical coordinate system and aligned, non-facial surface regions caused by an occluding object are determined at the occlusion detection phase. At this phase, a generic face model is used to locate a surface part which belongs to the occluding object. By the removal of these regions, one can obtain an occlusion-free face where occluded parts are removed from the original surface data. Occlusion-free faces contain actual facial surface data with missing regions. Therefore, it is possible to use them for identification purposes in two ways: 1) For restoration-based approach, they use face specific modeling via Gappy PCA that allows reconstruction of faces with missing parts. 2) For other approach, using occlusion-free faces directly without restoration, they compute dissimilarity scores on mutually available depth image regions of gallery and probe faces. In their work, they used the Bosphorus 3D face database that contains realistic 3D facial occlusions. In the Bosphorus database, from each of the 105 subjects, several types of occluded scans were collected systematically.

Peijiang Liu et. al [8] presents an efficient variant of the Iterative Closest Point (ICP) algorithm for 3D face recognition in the presence of occlusion. The new ICP variant improves the computational efficiency and robustness to occlusion changes. For the computational efficiency a facial surface is firstly described as a Spherical Depth Map (SDM), based on which uniform down-sampling can be conveniently applied to remove redundant vertices, aiming to decrease the consumed time of ICP. For occlusion

changes a rejection strategy is embedded into ICP to eliminate their impacts. The effectiveness of the proposed method has been demonstrated by face verification and identification tasks conducted on the Bosphorus 3D face database. The verification rate at 0.1% FAR reaches 85.8% while the rank-one identification rate achieves 97.9%. The process of downsampling has slight impact on the verification accuracy. The high rejection rate will lead to loss of identity information.

Nese alyuz et. al. [9] proposes a fully automatic 3-D face recognition system which is robust to occlusions. They basically consider two problems: 1) occlusion handling for surface registration, and 2) missing data handling for classification based on subspace analysis techniques. For the alignment problem, they employ an *adaptively-selected-model*-based registration scheme, where a face model is selected for an occluded face such that only the valid non occluded patches are utilized. After registering to the model, occlusions are detected and removed. By adaptively selecting the model, it is possible to discard the effect of occluding surfaces on registration. The occlusions are detected on the registered surfaces by thresholding point distances to an average face model. The training module works offline to learn the projection matrices from the training set of non occluded faces for different regions. In the classification stage, a masking strategy, which is called *masked projection*, is proposed to enable the use of subspace analysis techniques with incomplete data. The classification module uses the occlusion mask of the probe image to compute the masked projection, and projects the probe image to the adaptive subspace. The identification is handled in the subspace by 1-nearest neighbor (1-NN) classifier. The proposed system is evaluated on two main 3-D face databases which are Bosphorus and UMD-DB that contain realistic occlusions. The main disadvantage of the proposed method is that if occlusion is so large the nose area is totally invisible and the initial alignment becomes impossible. If the face is rotated by 30 degrees, it becomes impossible to find initial alignment.

III. PROPOSED METHODOLOGY

The proposed methodology is used for occlusion detection and removal from the occluded face using block matching algorithm. Then recognize the person from the database using principal component analysis.

A. Block Matching Algorithm

Let be the image in the database, the occlusion can be recovered by employing the block similarity measure scheme. For block matching process the probe image can be divided into number of non-overlapping blocks.

This can be represented as

$P = \{pb_1, pb_2, \dots, pb_{Nb}\}$, Where Nb represents the total number of blocks in the image.

The common type of region matching method is called as block-based motion estimation which uses rectangular blocks for motion estimation. Motion estimation is nothing but the process of obtaining the distance of the block of pixels between the two images. This distance is obtained by searching for the matching block which is done by Block Matching Algorithm (BMA). In our proposed

work, a novel block matching algorithm is described for discovering occlusion.

When we divide the image into block by block, some of the blocks are similar. To identify these similar blocks, we are using block matching algorithm. Here the block matching algorithm is used to detect the occlusion in the face image. The Euclidean distance measure is used to calculate the similarity between the images. For block matching process, we must compare each and every block of the query image and the images in the database. Let be the query image then we must divide the query image into block by block as described below.

$$q = \{qb_1, qb_2, \dots, qb_{Nb}\}$$

Then compare each block of the query image and the probe image in the database by employing Euclidean distance measure. This can be described as follows.

$$Ed_a = \sqrt{\sum (pb_1 - qb_1)^2 + (pb_2 - qb_2)^2 + (pb_3 - qb_3)^2}$$

Here 'a' is the total number of blocks in the image. This block matching process can be described in the following figure.

After calculating Euclidean distance between each block of two images, we perform soft thresholding technique to remove the occlusion. The pseudo code for soft thresholding is given as follows:

```

If  $Ed_a < thresh$  then
    Replace  $b_i$  with  $qb_i$ 
End if
    
```

This soft thresholding will recover the occlusion in the image. If $Ed_i = 0$ then both the blocks are similar. Otherwise there is an occlusion in the query image. So the occluded block is replaced by the original block in the database image. After identifying the occlusion we must extract certain features in an image.

B. Principal Component Analysis

By using the Principal Component Analysis (PCA), the normalized images can be recognized. Numerous possibly correlated variables are transformed into a smaller number of uncorrelated variables by a mathematical method known as principal components by PCA. Compute the eigen-faces from the training set by obtaining an initial set of R normalized images (the training set) and R' Eigen faces that correspond to the highest Eigen value are preserved. The average face for a given training set of images

$$\delta_1, \delta_2, \dots, \delta_R$$

can be defined as,

$$\Psi = \frac{1}{R} \sum_{n=1}^R \delta_n$$

The vector by which each face differs from average is

$$\zeta_i = \delta_i - \Psi$$

Finding the image k that minimizes the Euclidean distance \mathcal{E}_k is the easiest technique for identifying the face that provides the best description of an unknown input facial image.

$$\epsilon_k = \|\Omega - \Omega_k\|^2$$

where Ω_k is a weight vector that depicts the k^{th} face from the training set. If ϵ_k is less than certain selected threshold then the face is categorized as that of the person k otherwise it is categorized as an unknown face.

IV. RESULT

The proposed approach is implemented in MATLAB (R2009a) and 3d face recognition is performed using Face94 database under different occlusion. The results show that our approach gives high accuracy and robustness to occlusion.

For computing accuracy we first find FAR and FRR which is common way to find accuracy in biometric recognition. FAR is percentage of incorrect acceptance and FRR is percentage of incorrect rejections.

$$\text{Accuracy} = 100 - \left[\frac{(\text{FAR} + \text{FRR})}{2} \right]$$

For computing accuracy we test our approach with different number of percentage the face is occluded and also computing time to recognize person from the training database.

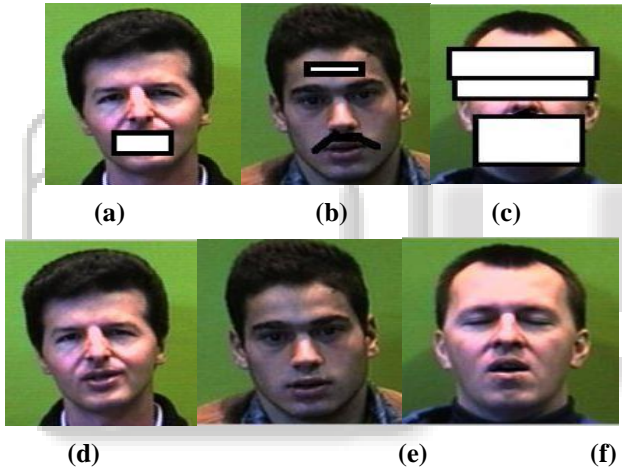


Fig. 1 (a) face with 10% occlusion (b) face with 30% occlusion (c) face with 90% occlusion (d) recognized face of (a), (e) recognized face of (b), (f) recognized face of (c).

Occlusion (%)	FAR	FRR	Accuracy
10	0	0	100
30	0.1	0.9	99.88
50	0.2	0.8	99.87
70	0.6	0.4	99.25
90	0.7	0.3	98.83

Table 1: Accuracy of proposed algorithm with number of occlusion in percentage

Percentage of Occlusion(%)	Time(sec)
10	4.9337
20	5.9118
30	10.1087
40	12.6498
50	15.7834

Table 2: Time taken to recognize face from the Database with number of occlusion in percentage

V. CONCLUSION

3D face recognition has matured to match the performance of 2D face recognition. When used together with 3D, it makes face a very strong biometric. In this paper, we proposed method for occlusion detection and removal method for 3d face recognition. For occlusion detection and recover face used block matching algorithm. For face recognition used principal component analysis. The results show that this approach improve recognition accuracy and robustness to occlusion.

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