Algorithms and Techniques used for 3D Face Recognition in the Presence of Expressions and Occlusion (ATFRPEO)

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Abstract— The purpose of this study is to enhance the algorithms towards the development of an efficient three dimensional face recognition system in the presence of expressions as well as for occluded face. The overall aim is to analyze patterns of expressions based on techniques relating to feature distances and also to segment the human face into non-occluded and occluded part of the occluded human face image. Here we are using two steps the first step is to recognize the face in different patterns of expressions and the second step is recognizing the occluded face. The first process can be obtained by using Euclidean distances, geodesic distances and regression models. And the second process is obtained by using Mean Based Weight Matrix (MBWM) algorithm.

Index Terms: Face Recognition; Feature Distances; Expressions; Regression Analysis, MBWM, support vector machine, SLBM, occlusion, LBP

I. INTRODUCTION

The 3D face recognition techniques have drawn people's attention. Many researchers have moved towards 3D human face recognition techniques. 3D face recognition is based on 3D images in which either the shape (3D surface) of the human face is used individually or the combination with the texture (2D intensity image) is used for the purpose of recognition. The images which are captured from camera can be represented in point clouds, triangle meshes or polygonal meshes and texture information to get a 3D facial image

There are several procedures to be carried out. The initial step is the face detection. The extraction of a face image from a large scene or image or video sequences. The next procedure is face alignment, which involves aligning the face image with a certain coordinate system. These procedures can be accomplished by several key tasks: the first task is the development of model and representation of facial surfaces. Second: extraction of 3D facial features (Feature extraction is to localize a set of feature points associated with the main facial characteristics).

Third, algorithm and methodology used for 3D facial surface data in an efficient way.

Next the major issue is on the problem of occlusion by other objects or apparels such as sunglasses, carves, mask becomes eminent. Thus a robust algorithm for occluded faces is required for real applications.

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II. BACKGROUND

Face recognition under expression variations is required in some applications and over last two decades many computer vision researchers have been attracted to focus on the problems of recognizing faces under expression variations. We have used two types of deformable models expression specific and expression generic to represent facial images in the presence of expression variations and pose variations. Basically mapping a deformable model to a given test image involves two types of transformations: rigid and non rigid transformations. The cost function is formed by using a translation vector, Rotatation Matrix and set of weights for rigid transformations. We are comparing 3D face recognition with 2D face recognition system in terms of Accuracy Gain, Efficiency, Automation and Testing Database Accuracy gain

3D facial expression recognition independently or combined with other modalities, a significant accuracy gain of the 3D system with respect to 2D face recognition system must be produced in order to justify the introduction of a 3D system Efficiency : 3D acquisition captures and creates larger data files per subject which causes significant storage requirements and slow processing. The data pre- processing for efficient data must be addressed. Automation: A system designed for the applications must be able to function fully automatically. Testing Database: Larger and widely accepted databases for testing the performance of 3D facial expression recognition system should be produced. Lee *et al*. [9] propose an expression invariant face recognition method. They extract the facial feature vector and obtain the facial expression state by the facial expression recognizer from the input image. The two main strategies for expression transformations are direct and indirect transformations. Direct transformation transforms a facial image with an arbitrary expression into its corresponding neutral face, whereas indirect transformation obtain relative expression parameters, shape difference and appearance ratio by model translation. By transforming them into its corresponding neutral facial expression vector using direct or indirect facial expressions transformation, they compare the recognition rate of each proposed method based on three different distance-based matching methods, nearest neighbor classifier (NN), LDA and generalized discriminant analysis (GDA).

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AlOsaimi *et al*. [10] introduce a new definition called the shape residue between the non-neutral and the estimated neutral 3D face models and present a method for decomposing an unseen 3D facial image under facial expressions to neutral face estimates and expression residues based on PCA. The residues are used for expression classification while the neutral face estimates are used for expression robust face recognition. In a result, 6% increase in the recognition performance is achieved when the decomposition method is employed. Li *et al*. [11-13] use low-level geometric features to create sparse representation models collected and ranked by the feature pooling and ranking scheme in order to achieve satisfactory recognition rate. They intentionally discard the expression variant features, which are considered as higher-ranked. The recognition rate 94.68% is achieved. Expressions seem to occur in a real word scenarios as even subtle expression variations can be captured into the 3D acquisition system. It has been claimed that face expressions can affect the accuracy and the performance of face recognition systems since the geometry of the face significantly changes as a result of facial expression. In general, the six significant expressions, happiness, anger, disgust, surprise, sad and fear, which make an adverse effect on face recognition. The adverse influence of face expression on face recognition is listed by Bronstein *et al.* [14] and needs to be solved no matter what dimensions face representation is being used (2D or 3D). However, its nonlinear nature and a lack of an associated mathematical model make the problem of face expression hard to deal with. There is no doubt that some progress has been made to solve this problem existing in 3D face recognition, but there are still some challenges remaining at this stage. For instance, Bronstein *et al*. [15,16] assume facial scans are isometric surfaces, which are not stretched by expressions so as to produce an expression invariant facial surface representation for recognizing faces. However, there is one constraint in that they only considered frontal face scans and assumed the mouth to be closed in all expressions, which is not considered realistic. Another issue with expressions is that there are less re-liable invariants when faces carry heavy expressions. In addition, another issue is how to optimize the combination of small rigid facial regions for matching in order to reduce the effect of expressions. Using rigid facial regions can improve the performance on a database with expression variations [17, 18]. The selection of rigid regions, however, is based on the optimal extraction and combination.

Researchers' attempts to reduce the computational cost have left another unresolved issue. Achieving less computational cost for real world applications has become a big challenge. Current studies intentionally use additional 2D texture information with an attempt to deal with expressions, which makes impact on computational time. In general, more information trained in 3D face data leads to more computational cost and time.

Some algorithms can work on the verification process with a time cost of about 10 seconds on a normal PC [18], whereas efficient face matching with less computational cost is still a problem when dealing with a large gallery with thousands of faces. In addition, modeling relations between expressions and the neutral by expression variant features and combining with expression-invariant features still remains a research question.

3. 3D Face Databases

The development of face recognition systems somehow relies on face image databases for the purpose of comparative evaluations of the systems. With the techniques of 3D face capture rapidly developing, currently more and more face

Figure 3. Illustration of the contour shape features describe

face elements, *i.e*. contour shape of eyebrows, eyes, nose and mouth**.**

We utilize two intrinsic geometric descriptors, namely geodesic distances and Euclidean distances, to represent the facial models by

Describing the set of distance-based features and contours.

The intrinsic geometric descriptors are independent of the chosen Coordinate system. We can observe that not all the distance vectors are invariant to Expression variations. For example, the mouth opening (G) in Figure 2(b) shows a change of a distance vector caused by an open mouth, when the face of the same individual changes from neutral to a laugh expression. However, there are some certain distance vectors that remain stable under expression variations, for example, the eye width (C) in Figure 2(b). Thus, for the distance based features, as we mentioned, we consider A, B, C and D distances in the top region as expression-invariants since they are insensitive under expression variations, whereas E, F and G are considered as expression-variants. We utilize Euclidean distances as the geometric descriptor to represent the set of distance- based features.

III. GEOMETRIC DESCRIPTORS

4.2.1. Euclidean Distance

In general, the distance between point p and point q in Euclidean n-space is

$$d_{e(p,q)} = \sqrt{\sum_{i=1}^{n} |p_i - q_i|^2} \qquad (1)$$

Where n is the dimension of Euclidean space. Specifically in this case, the Euclidean distance between points p and q in three dimensional Euclidean space is

$$d_{e(p,q)} = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + (p_3 - q_3)^2} \qquad (2)$$

The face model in the database comprises a triangle mesh, which is discretely defined to be a set of connected point clouds.

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The geodesic distance computation of tri angle meshes is initialized by one or more isolated points on the mesh and the distance is propagated from them. More specifically, the geodesic distance of discrete meshes is considered as a finite set of Euclidean dis- tances between pair-wise involved vertices. Thus, an- other geometric descriptor, geodesic distance, is utilized

in our feature sets. Geodesic distance is capable of rep-resenting the contour shape features on the discrete meshes. Similarly, the selected contour features contain expression-invariants and expression-variants. The eye contour and the mouth contour are sensitive to expression variations. However, the eyebrow contour and the nose contour comparatively remain stable during expression variations.

4.2.2. Geodesic Distance

On a triangle mesh, the geodesic distance with respect to a point turns out to be a piecewise function, where in each segment the distance is given by the Euclidean distance function. Thus the geodesic distance computation is initialized by one or more isolated points on the mesh and the distance is propagated from them.

$$d_{g(p,q)} = \sum_{i=1}^{n} d_{e(p_i,q_i)} \quad (3)$$

Where (), *gpq* is geodesic distance of a contour, (),*iiepq* is the Euclidean distance between two points and *n* is the number of control points of each contour. *d*

Depending on the different facial feature extraction methods, the slight influence of face sizes and different scales of the faces can be eliminated, either by normalization or by preprocessing before the recognition process. Thus, in addition to the geometric descriptors derived from the face models, we also consider defining two distance-based features to avoid the face alignment process and the normalization process.

We introduce a distance-based feature for normalizing the set of seven distance-based features, which is considered as a stable expression-invariant feature, as shown in Figure 4(a). In order to be consistent with the geometric descriptor used for the features, we utilize Euclidean distance to represent the feature, named *N*1 Thus seven normalized Euclidean distances are derived by the ratios of seven Euclidean distances to *N*1. Similarly, since geodesic distances are not scale-invariant, the next step is to normalize each geodesic distance by another distance-based feature [20], the eyes-to-nose distance, as shown in Figure 4(b), *i.e.* *N*2, sum of geodesic distances between the nose tip and the two inner eye corners. This guarantees invariance with respect to scaling and facial sizes under expression variations. Thus, for the set of contour shape features, this stable expression-invariant feature, *N*2 is represented by geodesic distance descriptor to ensure its consistency with the descriptor for the con- tour shape features. Deriving six normalized geodesic distances is accomplished by the ratios of the six geodesic distances to *N*2. Thus, the geometric descriptors for the whole set of features are comprised of two sets of ratios. Meanwhile, the attributes of the ratio-based geometric descriptors that are unique to each face model are investigated and

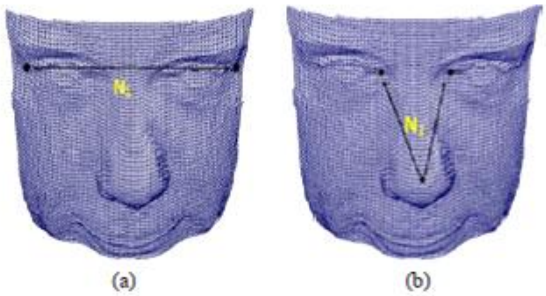

Figure 4. Illustration of two distances for normalization of two feature sets. (a) For distance based feature set; (b) For the contour shape feature set.

Proved before carrying out the next step. Compared to the commonly used descriptors in [14,21], our geometric descriptors benefit from fast computation due to their simplicity. In the next section, we adopt regression models to learn the relationship between pair-wise expressions based on the combination of these thirteen ratios based geometric descriptors.

4.3. Regression Analysis Models

The regression analysis model is utilized for analyzing the variables and modeling the relationship between them. Recently, regression analysis has been imported and applied in the face recognition area [22, 23]. In this chapter, we evaluate two types of regression model: partial least square regression and multiple linear regressions. Specifically, we employ them to learn the correlation between pair wise expressions and predict the 3D face neutral shape information for dealing with the problem of matching faces under expression variations.

4.3.1. Partial Least Square Regression

In this section, we will introduce a commonly used regression model that will be used to train and predict the feature set when the face models are neutral. Owing to the multiple dimensions of the involved variables, *i.e.* the total number of the ratio-based geometric descriptors, we will use a subspace regression model based on latent variables, named partial least square (PLS) [24].

X refers to a vector with the independent variables (predictors) and *Y* refers to a related vector of the de-pendent variables (responses).

$$X = TP + E,$$
$$Y = UQ + F,$$
$$U = BT + \varepsilon,$$

X is a matrix of predictors and *Y* is a matrix of responses. *E* and *F* are the error terms. There is a linear relation between *T* and *U* given by a set of coefficients B. A number of variants of PLS exist for estimating the *T*, *P* and *Q*.

The goal of PLS is to predict *Y* from *X* using a common structure of reduced dimensionality. For this pur pose, PLS introduces some latent variables:

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$$\{T_i\} = T_1, \cdots, T_k, \quad \{U_i\} = U_1, \cdots, U_k, \tag{5}$$

T and *U* preserve the most relevant information of the interaction model between *X* and *Y*.

Second the Major issue in 3D face recognition system is Occluded face

The conventional holistic approaches, such as PCA, LDA and ICA, are not robust to partial occlusions. Also, local feature based methods are less sensitive to occlusion detection. A number of local feature-based and component-based methods were proposed for dealing with the occlusion problem. The high dimensional data set of the local patch is then reduced using PCA.

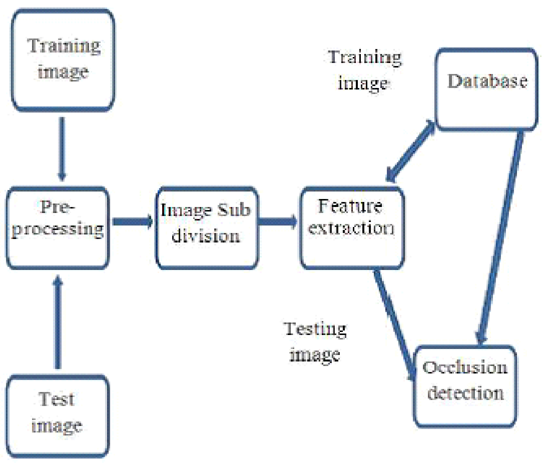

Fig. 1: Outline of occlusion detection process

IV. MATERIALS AND METHODS

Occlusion detection: The occlusion detection is based on Mean Based Weight Matrix (MBWM) algorithm. In order to get the discriminative features for face detection process, face image is segmented into different regions in a face image so that the features of only the non-occluded region which alone can show variation will be used for face detection which would improve the efficiency of the face detection system. Here,an occlusion detection algorithm based on subspace division is proposed.

Subdivision of a face image: Partial occlusions in face images usually occurs when the subjects wear adornments like sunglass or scarf, or when faces are covered by other objects such as hands, cup, mask and so on. In order to detect the locally occluded regions in a face image, the face image is subdivided into number of facial components. The number and the shape of the components depend on the nature of the occlusions. The face image is subdivided into 2, 4 and 6 segments. The discriminative features for each segment are then calculated. This study focuses on the occlusion detection on the face covered by medical mask. When the face image is subdivided into two equally halves as shown in Fig. 2 the lower Segment is used for detecting mask. Once the face is divided discriminating features are extracted from both the occluded and non-occluded part of the face image. These features are then fed to an SVM classifier for determining whether an occlusion is present or not.

Occlusion detection using LBP: Occlusion detection of a given face image is accomplished for each local patch independently by employing pattern classification framework. Local Binary Pattern (LBPs) which was first proposed by (Ahonen *et al*., 2006) was originally designed for texture description. Still, it has shown very good performance in many other tasks and one of the

Most important application areas are facial image description. The basic LBP operator labels the pixels of An image (Ip) by thresholding each 3´3 pixel neighborhood of the input image with the center pixel value (Ic), multiplying the threshold values by weight (powers of two) and summing them. The operation of the basic LBP operator is illustrated in Fig. 3. Thresholding is done using the centre pixel as in

$$f(I_p - I_c) = \begin{cases} 1 & I_p \geq I_c \\ 0 & \text{Otherwise} \end{cases} \tag{1}$$

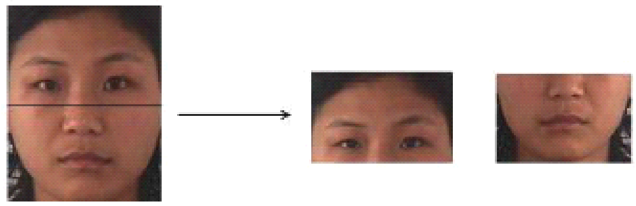

Fig. 2: Locally subdivided face

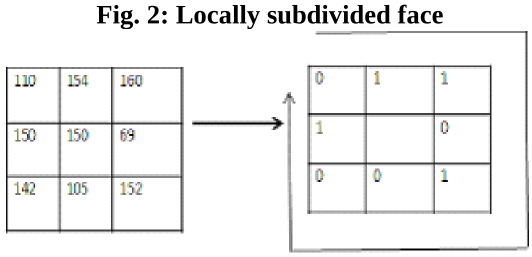

Fig. 3: LBP operator. LBP = (01101001)2 =150

Weights are then assigned and the LBP values are obtained using Eq. 2 and the values are summed to obtain the LBP values for the 3´3 matrix. The LBP feature thus obtained are considered for classification purpose:

$$LBP = \sum_{P=0}^{7} f(I_p - I_c)2^P \tag{2}$$

LBPs have been very effective for image representation as it is being applied to visual inspection, motion detection and outdoor scene analysis. The most important properties of LBP features are their tolerance against monotonic illumination changes and their computational simplicity. The LBP operator mainly detects many texture primitives as spot, line end, edge and corner typically accumulated into a histogram over a region to capture local texture information.

Occlusion detection using SLBM: The simplified local binary mean as proposed by (Priya *et al*., 2012) involves three steps which include subdividing, thresholding and weighing. First, a 3´3 sub image is cropped .The pixel values are represented as Ip. Thresholding is done using the mean of the 9 elements of the 3´3 sub image (Im). Thresholding is done based on the rule given in Eq. 3:

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$$f(I_p - I_m) = \begin{cases} 1, I_p \geq I_m \\ 0, \text{Otherwise} \end{cases} \quad (3)$$

Weights are then assigned and summed to obtain the SLMB values for the 3´3 matrix using Eq. 4. The SLMB feature thus obtained are considered for classification purpose:

$$SLMB = \sum_{P=0}^{7} f(I_p - I_m)2^P \quad (4)$$

The SLMB features are thus calculated. Many images of different types can have similar histograms, because, histograms provide only a coarse characterization of an image. This is the main disadvantage of using histograms. So, the statistical features such as mean and standard deviation of the SLMB features are calculated.

Occlusion detection using MBWM: In SLBM, thresholding is exactly at the value of the central pixel . This makes it to be sensitive to noise, especially in near uniform image regions. Many facial regions are relatively uniform; it is potentially useful to improve the robustness of the underlying descriptors in these areas. So, the SLBM is extended to mean Based Weight Matrix (MBWM) The mean based weight matrix involves three steps which include subdividing, thresholding and weighing. The 3´3 pixels of the image are replaced by a 3-valued functionas given in Eq. 5:

$$f(I_p - I_m) = \begin{cases} 2, I_p > I_m \\ 1, I_p = I_m \\ 0, \text{Otherwise} \end{cases} \quad (5)$$

Weights are then assigned and summed to obtain the MBWM values as in Eq. 6 for the 3´3 matrixes:

$$MBWM = \sum_{P=0}^{7} f(I_p - I_m)2^P \quad (6)$$

The MBWM features are thus calculated. The first order statistical features such as mean and standard deviation of the MBWM features are calculated. These features are used for classification.

Support Vector Machine (SVM) classifier: As a powerful machine learning technique for data classification, SVM performs an implicit mapping of data into a higher (maybe infinite) dimensional feature space and then finds a linear separating hyper plane with the maximal margin to separate data in this higher dimensional space (Chang and Lin, 2012). Given a training set of labeled examples {(xi, yi), i = 1, 2 ……l} where xi Є Rn and yi Є {-1, 1} a new test example x is classified by the function as in Eq. 7: training set of labeled examples

{(xi, yi), i = 1, 2 ……l}

where xi Є Rn and yi Є {-1, 1} a new test example x is classified by the function as in Eq. 7:

$$f(\chi) = \mathrm{sgn}\left(\sum_{i=1}^{l} \alpha_i \, y_i \, K(x_i, x) + b \right) \quad (7)$$

where, ai is the Lagrange multiplier of a dual optimization problem that describes the separating hyper plane K (xi, x) is a kernel function and b is the threshold parameter of the hyper plane. The training sample xi with ai > 0 is called support vectors and SVM finds the hyper plane that maximizes the distance between the support vectors and the hyper plane. Given a non-linear mapping Φ that embeds the input data into the high dimensional space, kernels have the form of K (xi, xj) = (Φ (xi), Φ (xj). SVM allows domain-specific selection of the kernel function. Though new kernels are being proposed, the most frequently used kernel functions are the linear, polynomial and Radial Basis Function (RBF) kernels. SVM makes binary decisions. With regard to the parameter selection of SVM, the mean and standard deviation are chosen. These parameters provided the best accuracy. The generalization performances achieved using the two different kernels is discussed.

V. CONCLUSION

The fundamental face recognition technique in the presence of expression variations was based on a correlation learning model which generated a non neutral model with a neutral model in order to match non neutral faces to neutral faces. One of the issues pointed out by the researcher was reducing the computational cost. Rather than taking a large number of features into account, we intended to use the limited feature set representing contour information and face structure information. We built a novel framework of learning the correlation between various expressions and neutral with the limited feature and also we have concentrated on Occlusion problem, which has been researched relatively less than illumination and pose problems in face recognition, is discussed. SLBM and MBWM are the two algorithms proposed for partial occlusion detection. Locally occluded areas in faces are detected using SVM classifier and hence classified as occluded and non-occluded face images.

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