Fine Registration of 2.5D Faces by using Modified Iterative Closest Point Algorithm

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***Abstract*—Face Recognition is the most competent area in the field of image exploration and computer vision. The good face recognition system is essentially depends on the feature extraction and fine registration. This paper presents the Modified iterative closest point algorithm for fine registration of 2.5D faces. In which two classical iterative closest point algorithms are integrated in which first iteration completes the estimation of alignment computation followed by second iteration does the refinement.**

Keywords—face recognition, alignment, iterative closest point.

I. Introduction

Most popular applications of image analysis and understanding, in recent times face recognition gained a lot of response, mainly during the past years. Actually the current machine recognition systems have reached a certain level of maturity; their success is limited by the conditions imposed by many real applications. Reasons to prefer face recognition rather than other biometrics in computer vision are physical interaction are not required and it is accurate and robust. As Figure 1 shows, Feature Extraction is the crucial portion of the every successful face recognition system [1]. 2.5D is nothing but a one kind of range image which gives dimensions of x, y and z plane values shape representation which holds at most one depth value with respect to z axis or plane for every (x, y) value plane. Human face is nothing but a three-dimensional objects whose face image or appearance (exterior texture) is sensitive to the pose of head, luminance and facial expression variation conditions. 2.5D scan is a representation of the 3D surface shape information which is the internal anatomical structure of a face [2]. Fig. 1 shows the general configuration of the typical face recognition system.

In this paper we described a modified method which works with two typical ICP algorithms of Besl and Chens to improve robustness of existing face recognition system. Firstly, Besl method performs or completes the estimation of alignment computation (point-to-point matching) followed by the Chens method does the refinement (point-to-plane matching).

This paper arranged as, Section 2, described the related work. Followed in Section 3, feature point extraction is described. The Integration of both the methods is presented in Section 4. Section 5 focuses on the Mathematical approach used and experimental results and finally Conclusions and Future Work are provided in Section 6.

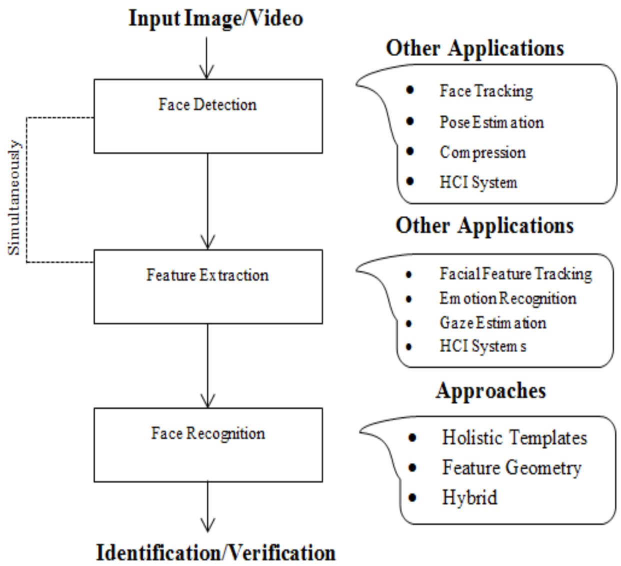

Fig. 1. General face recognition system configuration [21]

II. Related Work

Face recognition by using range images has been addressed by different ways some of them are addressed here. Cartoux et al. used extracted faces profiles from the 3D range images for face recognition [3]. Gardon explored the depth and curvature feature based face feature extraction [4]. Lee and Milios used the Extended Guassian Image (EGI) for convex region representation in which images are segmented to obtain the convex regions. Matching the facial features of the two face images are depends on the defined similarity metric between two convex regions [5].

Chau et al. utilized point signatures for frontal face scans with expression variation, which was works like a 3D face recognition problem of non-rigid surfaces [6]. Tanaka et al. used a method which is based on the curvature information of the faces in which problem of rigid free-form surfaces nothing but 3D shape recognition is considered [7]. Hesher et al. used PCA for the estimation of the probability models for the coefficients [8]. Bronstein et al. described an algorithm which is constructed on the geometric invariants with an attempt to deal with facial expression dissimilarities for face recognition system [9]. Chang et al. used combination of texture and shape information by applying PCA to both 2D and 3D data [10]. Pan et al. does alignment and matching of two range images by using the partial directed Hausdorff distance [11].

III. Feature Point Extraction

Feature point extraction is the start of the procedure. Feature point extraction aims to rigid transformation calculation which needs at least three corresponding points. After at least three points identified, using integration of rigid transformation matrices the transformations will be done [12] which aligns the two scans. Which focus on an analytic solution to the specific problem of three corresponding points in the two corresponding poses, and an analytic measurement of the root mean squared (RMS) distance/error between the points of the resultant poses. Derive the mathematics of the solution and prove that the intuition is correct. Intuition derivation procedure as stated in Weinstein is as following in which $a{:}\,(a1, a2, a3)$ are points from the pose to be transformed and $p{:}\,(p1, p2, p3)$ are points from the fixed posed.

1. Translating a so its centroid C_a aligns with the centroid of p ,C_p
2. Find the rotation matrix which aligns the normal $\overrightarrow{N_a}$ to $\overrightarrow{N_p}$.
3. Transformations performed after the rotation, the triangles are located in the same plane, and have the same centroid. C =same points (pC and aC); normal $\overrightarrow{N}$.
4. Rotate the triangle a which is new one, about $\overrightarrow{N}$, in direction to decrease the summed-squared-distance between vertices.
5. Determine a scale factor s, for the triangle a, and scale the distance between its vertices $(a1, a2, a3)$ and the centroid C in order to once again minimize the distance between the triangles. Resultant transformed triangle as $\ddot{a}$.

Also, specific feature points are required for grid of control point's alignment.

Local shape values at every point contained by the 2.5D image is determined [13]. The local shape indexes at each point of 2.5D scan are selected as feature points [14]. In which shape index at point p is calculated using minimum and maximum local curvatures k_1 and k_2 respectively (eq.1).

$$S(p) = \frac{1}{2} - \frac{1}{\pi} arctan \frac{k_1(p) + k_2(p)}{k_1(p) - k_2(p)} \qquad (1)$$

In which shape index varies from 0 to 1 value. Table I states the values and their respective shape [13].

IV. Coarse Alignment

Inside eye, outside eye and mouth when these minimum three points have been known, a rigid transformation can be prepared among the points [12] which involve the least square appropriate between the triangles prepared from the both sets of three points. The first set of three feature points (a) is transformed into the same location as the second set of feature points (p) . The rigid transformation is composed of a series of simple transformations:

$$TT = T_{c_p} \cdot B_p{}^t \cdot S \cdot \theta \cdot B_A \cdot T_{C-a} \qquad (2)$$

where,

TT – Total transformation from feature points a to feature points p.

T_{C-a}– Transform points a to an origin at center of the triangle formed by the vertices of the triangles.

B_A– Transform world coordinates into coordinates based on basis vectors of set a

θ – Optimum rotation to align point vertices into basis vector of set P.

S – Optimum scaling between point vertices and

$B_p{}^t$– Transform from p basis vectors back into original world coordinates.

T_{c_p}– Transformation from the center of p vertices into the original world origin.

V. Fine Alilgnment

In coarse alignment two facial scans are ranged based on three pairs of anchor points. We only focus on surface matching and in coarse alignment stage because of the errors of localization the scans are not well registered which is required for surface matching. Fine registration is performed using modified iterative closest point method. But before applying ICP, two pre-processing steps are necessary to check, determination of overlapping area and selection of control points [15], [16].

For fine registration process we used the Iterative Closest Point (ICP) framework [17], [18], [19]. Typical Iterative Closest Point working procedure is as, first step does control point's selection in one point set after in second step that find the correspondence means finding closest point related to the points in other point set. Third step calculates the optimal transformation based on the correspondence calculated in the second step. Finally, transform that points and repeat the procedure from step 2 until convergence.

Start of the modified ICP from initial estimation of rigid transformation derived in the coarse alignment stage of typical iterative closest point procedure. In Besl’s method, the point-to-point distance methos is used and the close-form solution is delivered when scheming the transformation matrix through the iteration. Advantage of this algorithm is that it is fast to process. The Chen’s method, the point-to-plane algorithm states that when two tangles are near to each other the finest approximation is performed by the point-to-plane method for the calculation of the exact distance between the two surfaces [20]. But the point-to-plane method’s distance results in local minima less susceptibleness. Also, point-to-plane distance is not as fast when compared with point-to-point because it takes more time.

Modified Iterative Closest Point method uses integration of these two algorithms in which algorithm has two iteration. In first iteration by using Besl’s method an estimation of the alignment computation is performed continue in second iteration Chen’s method ensures refinement [14]. We formed rectangles instead of triangles in coarse alignment which helps us to improve rigid transformation. In the results section figure of grid control points selection shows the rigid transformation correlated faces.Distances of this two different methods improves registration results than their individual working results.

The two facial scans from the same subjects results in a better registration than the subjects from the different subjects.

VI. Results

Figures 2 and 3 shows the results in which Fig. 2 shows the feature points extracted from the 2.5D face and Fig. 3 shows the rigid area extracted from the 2.5D face with fine registration procedure.

Fig. 2. Feature point extraction of different 2.5D faces.

Fig. 3. Grid of control poins selection.

Theoretically closest point search has best case complexity of $O(N_p)$ and practically by combining two typical iterative closest point algorithms results in complexity $O(p * e^t)$.

VII. Conclusion

This paper presented a reconstututed iterative closest point algorithm for robust fine registration. This method utilizes shape information. Two iterations are performed in which first iteration for the estimation and second iteration for refinement results in a robust and efficient fine registration solution.

This is the best solution for the fine registration. We plan to improve the coarse alignment by setting constraints for more robust face recognition system.

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