Disturbance-Region Removal on Landmark-less Registration of Craniofacial Images Acquired by CBCT and 3D Photography

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Abstract— Superimposition of cranio-maxillofacial images acquired from cone-beam computed tomography (CBCT) and facial images acquired from three-dimensional photography (3D photography) can assist in diagnosis and surgical planning. Conventional approaches individually identified prominent facial landmarks on both modalities, respectively and assessed their correspondence. Considering, however, variation of facial expressions or drastic feature distortion when the face or head was imaged at different timing, landmark registration can become challenging. This paper proposes a disturbance-region removal (DRR) procedure to improve the efficacy of registration. The disturbance regions (DRs) are defined as those exhibiting strong responses in the concavity intensity maps that are computed from the facial surface mesh. Following this identification process for the DRs, an adapted symmetric region growing algorithm is used to form the connected DRs that are to be removed prior to superimposition of both modalities. The results show a twenty-eight percent better match of overall correspondence of the facial fiducial markers. Instead of being the registration guides in conventional approaches, in this study the fiducial markers are employed as only a means to assess the performance of registration.

Keywords— CBCT; concavity intensity; registration; superimposition; disturbance-region removal; cranio-maxillofacial

I. INTRODUCTION

Cone-beam computed tomography (CBCT) captures images for diagnosis and planning the treatment, simulation, and navigation in cranio-maxillofacial (CMF) surgeries. Lack of accuracy and texture of the skin surface is, however, the main drawback of CBCT images [1].

Fusion of high-resolution three-dimensional (3D) photographs, e.g., 3dMD images, of the face with the skin surfaces derived from CBCT images is a possible solution, as shown in **Figure 1**.

For the fusion process, conventional clinical approaches usually determine facial features/landmarks at first and perform superimposition of the images acquired from both modalities in the next [2-4]. Consider, however, facial expression that varies over time changed the locations of prominent facial landmarks. This would make the registration unreliable. Specifically, landmarks can be greatly displaced in case of superimposing pre- and post-surgical images [5-7]: facial features may be shifted, distorted or even missing after a surgery [8].

This paper proposes a robust disturbance-region removal (DRR) based procedure, as shown in **Figure 2**, which is without the need of identifying facial landmarks. The procedure requires minimal manual interventions to perform superimposition. With the removal of the prominent facial features that are usually subject to variable facial expressions or surgical operations, the facial parts left on both 3dMD and CBCT images are iteratively convolved to determine the optimal superimposition result.

In the remainder of the paper, steps of the proposed procedure and the related algorithms shown in **Figure 2** will be elaborated in detailed in the Materials and Methods section. The quantitative results and comparisons are presented in the Results section. The Discussion section interprets the results and gives some insights from the further analytical process. The Conclusions section gives the concluding remarks.

(a) Frontal view

(b) Lateral view

Figure 1. Translucent views to the superimposition result of a pair of a three-dimensional photograph (via 3dMD imaging) and a CBCT image. Fiducial landmarks, as shown as black spots, are placed on the face before scanning and serve as the references to compute the correspondence of 3dMD and CBCT modalities.

Figure 2. Proposed superimposition procedure with disturbance-region removal (DRR).

II. MATERIALS AND METHODS

Ethical approval for this study was granted by the Institutional Review Board of Chang Gung Memorial Hospital, Taiwan. (102-1359B, 103-3130B, and 201600809B0).

In this study, 3D photographs (via 3dMD imaging) and the CBCT images are acquired from five individuals who have six fiducial markers attached on their faces before imaging. These fiducial markers are used as landmarks to measure the performance of registration. They are labelled as upper forehead (UFH), right upper forehead (RUF), left upper forehead (LUF), right lateral cheek (RLC), left lateral cheek (LLC), and chin (CIN) [9].

As a data pre-processing, the symmetric region growing (*SymRG*) algorithm is used and performed to extract the surface from the CBCT image and to segment (trim) out the interior volume structures of the head [10]. This *SymRG* algorithm allows a range of intensity variation of the face and forms a *connected head surface*. This pre-process can efficiently mitigate the computational loading that is required for superimposing the images of both modalities.

The novel procedure which is proposed involves an initial phase to generate the *3D convex hulls* (the top-left box as shown in **Figure 2**) [11], which are as the basis to compute the *concavity intensity maps* of the face (the bottom-left box) [12]. This phase begins with the use of the preprocessed data, which is the ‘connected head surface only’ CBCT image, which is the result from the region growing preprocess.

On the 3D convex hull, the *disturbance regions* (DRs) of the face are identified as those exhibiting strong concavity intensities, as depicted as brighter areas in the concavity intensity map, and they are removed prior to the subsequent phase (i.e., see the bottom-right box), which also include the fusion of both modalities [12, 13]. To ensure that the DRs are homogeneous and are strongly connected closures [7, 10], a second stage of *SymRG* is also implemented. Further, only regions whose volumes significantly deviate 5% from the head surface are considered as DRs; others are relegated as noise.

Then, an iterative closest point (ICP) algorithm is employed and used to determine the minimum displacement of the CBCT and 3dMD facial surfaces (the bottom-right box in as shown in **Figure 2**) [14, 15]. The upper-right box demonstrates a translucent superimposition result of the CBCT and 3dMD images.

The relevant algorithms which are implemented for the proposed procedure (i.e., for computing concavity intensity maps, symmetric region growing, and iterative closest point) are presented as follows.

A. Computations to Obtain the Concavity Intensity Maps

The concavity intensity of a cloud point is defined as the distance from the point to its nearest projection on the convex hull of the point cloud [11, 12, 16]. The proposed algorithm is adapted from [12] as shown in **Figure 3**.

```

// Given a point cloud P, triangulated mesh T, and a pre-specified radius r of searching sphere
// Compute and return a concavity intensity map Cim
Cim = Concavity_Intensity_Map(P, T, r):
    Cim = { } // Initialize an empty map
    for v in P:
        // Compute the normal vectors from v to neighboring triangular mesh with radius of r
        concavity_intensity_list = Compute_Concavity_Intensities(v, T, r)
        // determine the concavity intensity of v (CI_v) and its associated triangle ID (t_ID)
        [CI_v, t_ID] = concavity_cintensity_list.min()
        Cim[v] = [CI_v, t_ID] // add to the concavity intensity map

```

Figure 3. The Computational Algorithm to Obtain the Concavity Intensity Map.

B. Point-Cloud Based Symmetric Region Growing (*SymRG*)

Wan *et al.* defined a class of Symmetric Region Growing (*SymRG*) algorithms that are region-based segmentation methods and are insensitive to the initial seed assignment [10].

One of the advantages of *SymRG* is its computational efficiency, which is especially suitable for this study to deal with a great amount of cloud points that are present.

Summarizing the theoretical development of *SymRG*, without loss of generality, four properties are given below.

- *Property 1:* Consider $SymRG(\psi)$, such that $S(I, SymRG(\psi), A) = \bigcup_{k=1}^N R_k$, where I denotes the cloud points; A represents the seed set; $\psi = \langle I, X \rangle$ denotes the region's including (I) and excluding (X) criteria that are symmetric; R_k is the k th segmented region; $S(\cdot, \cdot)$ gives the segmented result. The replacement of certain seed by another point in the same region gives the equivalent segmentation result.
- *Property 2:* Given $SymRG(\psi)$ and seed sets $A, B \subset I$, both sets containing corresponding pairs of seeds in the same regions. There is at least one one-to-one region-growing path between every corresponding pair of elements in A and B if and only if $S(I, SymRG(\psi), A) \equiv S(I, SymRG(\psi), B)$.
- *Property 3:* Consider $S(I, SymRG(\psi), \mathcal{S})$, a complete segmentation algorithm based on symmetric region growing. $\mathcal{S}$ denotes the seed criteria, which can eventually derive the seed set. Scan the image of interest, I , sequentially. Grow regions from each scanned point by applying inclusion, I , and exclusion, X , criteria $\psi = \langle I, X \rangle$, until all image points have been visited.

Examine the resulting regions using $\mathcal{S}$. If any point p of a region satisfies criteria $\mathcal{S}$ for region R_i , then assign the region to R_i ; otherwise, relegate it to the background R_N . The resulting segmented image is $S(I, SymRG(\psi), \mathcal{S})$.

- *Property 4:* The region-growing process of a $SymRG$ is computationally separable.

$SymRG$ requires the region growing criteria be symmetric. In this study, distance of cloud points, difference of intensities, and connectivity check in the surface mesh are the only operators used to define homogeneity of a region; i.e., the corresponding region growing criteria are symmetric and, therefore, $SymRG$ is applicable to construct homogeneous disturbance regions.

In the proposed algorithm, the cloud points are sequentially grown and merged into regions in three consecutive phases, along x -, y -, and z -dimensions, respectively. A region table is built along the region growing process, while an equivalence table is used to merge those regions that exhibit connectivity when the higher-dimensional information is introduced. A general N -dimensional $SymRG$ algorithm is given in Figure 4.

```

// Given an N-dimensional image array with 2 elements I[1] and I[2]
//           I[1] stores the original image
//           I[2] stores the region label result
// Perform symmetric region growing with criteria  $\psi$  from seeds  $\mathcal{S}$ 
SymRG(I,  $\psi$ ,  $\mathcal{S}$ , n):
    if n==1:
        Construct_Region_Table( $\psi$ )                // region table from I[1]
        Initialize_Equivalence_Table( $\psi$ )          // equivalence table from I[1]
        Assign_Each_Point_with_Initial_Label()      // region labels stored in I[2]
    else:
        SymRG(I,  $\psi$ ,  $\mathcal{S}$ , n-1)
        Update_Equivalence_Table_with_Connectivity_Information(n) // per I[1]
    if n == N:
        Update_Each_Point_with_Label_by_Referring_to_Equivalence_Table() // in I[2]

```

Figure 4. The General N-dimensional Symmetric Region Grow Algorithm.

```

// Given two surface cloud points  $S$  and  $S'$ , we shall attempt to deform  $S'$  to match  $S$ .
// Determine the best deformation function  $F$  that results a minimal cost  $C$ 
For each point  $p_i$  on surface  $S$ , determine its corresponding point  $p_i'$  on surface  $S'$ .
    Consider an arbitrary initial deformation function  $F_j$ , such that the estimated  $\tilde{p}_i = F_j(p_i)$ .
    The cost  $C$  of mismatch of surfaces  $S$  and  $S'$  can thus be represented as:
         $C = \sum_i d(\tilde{p}_i, p_i') = \sum_i d(F_j(p_i), p_i')$ ,
    where  $d(\cdot, \cdot)$  is a distance function.
    Iteratively adjust  $F_j(\cdot)$  until the minimized cost  $C$  is reached.

```

Figure 5. The Iterative Closest Point Algorithm Used for the Optimal Superimposition.

C. Perform Superimposition with DRR Using Iterative Closest Point (ICP)

To optimally superimpose the CBCT and 3dMD images is equivalent to determining the best deformation function from one to the other [14, 15]. The ICP algorithm can be formulated as Figure 5.

In this paper, as the head surfaces with DRR are rigid, the Euclidean distance is employed as the distance function $d(\cdot, \cdot)$. As for superimposing non-rigid surfaces, the other “similarity” metrics among selected features can be used instead. Further, in case that a minimized C is difficult to reach, the process can be terminated either:

- 1) when the difference of costs between consecutive iterations (e.g., C_{t+1} for iteration $t+1$ and C_t for iteration t) falls under a pre-specified value τ ; i.e., $|C_{t+1} - C_t| < \tau$; or
- 2) when the maximum number of iterations is reached.

III. RESULTS

The observable results are obtained from an experiment. In the experiment, by using the data set which is sourced and introduced in the former part of Section 2, both the conventional approach and the proposed registration procedure are implemented as the control group and the study group, respectively, as to see and compare the results from superimposing the CBCT and 3dMD images using both methods.

The experimental design for the two groups that enables the comparisons is as follows:

- Landmark-based vs. landmark-less
 - Manually determine landmarks vs.
 - Semi-automatically generate convex hulls and compute concavity intensity maps
- Non-DRR vs. DRR
- Both employ ICP algorithm to determine best possible superimposition
- The Euclidean distances of six aforementioned fiducial marks (i.e., UFH, RUF, LUF, RLC, LLC, CIN) are used to assess the performance of both groups
- Student's T-test is used to compare the results from the control and study groups. The accuracy of each technique is calculated with Dahlberg's formula [17-19].

Table 1 shows the registration displacements for each studied case in the image data set, in the control group and the study group, in terms of the Euclidean distances measured (in mm).

IV. DISCUSSION

As can be observed from the main results shown in Section 3 and Table 1, in overall, the mean distance of the corresponding fiducial markers is $1.12mm$ in study group and $1.56mm$ in control group. There was statistical significant difference ($p < 0.01$) between the two registration techniques (by using the last experimental step in Section 3).

In the table, the empty cells mean the cases in which the suitable locations to place the fiducial marks are missing on the image, due to any probable reason. For these cases, the displacements for the control and study groups are both ignored.

An interesting observation is that for all testing fiducial marks, all values in the study group are less than $2mm$ except for the only one value for the LUF mark (i.e., 2.01, see the LUF-study column). In contrast to this, there are seven distance values in the control group that are greater than $2mm$, and a distance of registration displacement for the UFH mark is observed even more than $3mm$ for case 5.

The above observation is reflexive to the following fact: the study group presents 28% better superimposition performance in average than that of the control group.

In a similar fashion, when the average displacements of the control and study groups are calculated along the x -, y -, and z -coordinates individually, the study group exhibits an average of $0.55 mm$ displacement, while the control group exhibits an average of $0.81 mm$ displacement ($p < 0.001$). And, no statistical significance of differences is found among along the x -, y -, and z -coordinates.

Therefore, by using the real CBCT and 3D photographic image data sets which is sourced from the operational database of a large scale hospital, from the designed experimental flow and from the results obtained from the experiments using either the direct distance measures or the statistical tests, it would be observed that the proposed DRR-based procedure is a suitable approach for solving and optimizing the encountered problem. It offers a land-markless method for the physicians to perform the image registration process for the different types of 3D images or for the 3D images that are imaged at the different timings. And, the proposed procedure is shown more efficacious than the conventional one, according to the results. This is perhaps because of the appropriate selection of the used methods/algorithms and a suitable ‘hybrid’ of these methods.

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Moreover, as such a hybrid-methods superimposition procedure can be easily computerized because the involved phases use computer algorithms, future clinical DSS

implementations is therefore expected, and this should be an appropriate way to increase the productivity of the physicians [20].

TABLE 1.
Registration displacement (mm) between CBCT and 3dMD images

Case	UFH		RUF		LUF		RLC		LLC		CIN	
	Control	Study	Control	Study	Control	Study	Control	Study	Control	Study	Control	Study
1	1.93	0.59	1.58	0.90	2.18	1.49	2.22	1.56	1.78	1.11		
2	2.43	1.26	2.44	1.40	2.43	2.01			0.82	0.14	1.15	0.93
3	0.91	0.99	0.75	0.75	1.08	0.89	0.41	0.35	1.57	1.08		
4	1.11	1.52	0.87	0.49	1.56	1.35	1.40	0.91			1.17	1.29
5	3.22	1.96	0.49	1.56	2.36	0.94					1.2	1.12
Avg.	1.92	1.26	1.23	1.02	1.92	1.34	1.34	0.94	1.39	0.78	1.17	1.11

V. CONCLUSIONS

The proposed superimposition procedure with DRR manifests itself is promising performance, compared to the conventional approaches, in the following perspectives:

- Better accuracy of registration
- Robust with respect to possible variation of facial expressions when images are acquired at different timing
- Reproducible
 - No manual interaction is required
 - Novel algorithms to compute concavity intensity maps
- Applicable to pre- and post-surgical assessment
 - DRR is robust to cope with significant alternation of facial features

Finally, given the original novelty of this study, the future work of this study involves, but not limited to, DSS implementation (see Section 4), algorithmic improvement or replacement (e.g., replacing a used algorithm with a more efficacious or efficient one), empirical/evidence-based verification to the procedure/models/algorithms with a larger scale of data set (e.g., sourcing another set of dual-image cases from other hospitals), etc.

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Conflicts of Interest: The authors declare no conflict of interest.

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