Multimodal Tracking of Threedimensional Maxillo-dental Changes of Bones and Soft-tissues Over Time

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Main Issues

- How to segment volumetric data?
- How good is CBCT geometry?
- How to combine CBCT with Photogrammetry?
- How to do long-term registration?
- More modalities
- Conclusion



3D Difference After Six Months



From Density to Geometry



Volumetric Density Data

Geometry Using Region Growing



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Segmentation(1)

Problem: Structures easily detected by the human eye are difficult to specify for a computer

 Many different segmentation approaches and variations available

 Specific image acquisition protocols can ease segmentation difficulties, i.e. contrast agent



Segmentation(2)

- Automatic segmentation frequently segments too much, or not all structures
- Manual segmentation is usually too expensive for daily practice
- Semi-automatic segmentation with little interaction only: can consist of several steps



Segmentation(3)

- •Typical medical semiautomatic segmentation algorithm is **3D Region growing**
- Specify seed point inside structure of interest
- Specify threshold interval which describes material interfaces
- Successively selects neighbouring voxels until threshold interval is violated



Segmentation(4)

Potential problems of 3D region growing:

- Inappropriate threshold interval
- False/missing connections due to partial volume effect or signal attenuation
- Resolution too low
- Contrast too low; good contrast: feature intensity high, surrounding intensity low



AMMI Lab. Laser Scanner





Cone Beam CT vs Laser Scanner





Final Precision

- An average difference of 0.12 mm with a two sigma variance of 0.4 mm was observed. There were no systematic biases observed.
- In a similar geometric accuracy study with a different CBCT unit, Marmulla et al. found an average image deviation of 0.13 mm which was below than the voxel size of 0.18 mm.
- Although a difference between CBCT and LS measurements were identified; CBCT appears to be sufficiently accurate to be used as a clinical tool.







Problem with CT Segmentation





Determining an Optimal Threshold

CBCT scans were taken on four different days at three different times

- COLD when the machine was first turned on
- I hour after an hour of the machine being in use
- 4 hours after four hours of the machine being in use
 For each time the CBCT was used and an optimum threshold was determined
 According to the data collected, the threshold is dependent on both time and date





Signed Error of Different Thresholds on CBCT June1 (COLD)





Signed Error of Different Thresholds on CBCT June1 (1hr)





Signed Error of Different Thresholds on CBCT June1 (4hrs)





How Different Are CT & CBCT (COLD)?





How Different Are CT & CBCT (1 hour)?





How Different Are CT & CBCT (4 hours)?





Factors Influencing Precision?

- Elliptical Interpolation for normal CT
- CT Reconstruction Algorithm
- Type of Sensors (CBCT vs Fan Beam CT)
- Sensor setting
- Filtering
- Segmentation Algorithm
- Signal Contrast
- CT Calibration



CBCT and Photogrammetry

3D Digitizing Facility Built at the UofA Faculty of Dentistry





Stereo Pairs of 3dMD





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Registration of Skin and CBCT Using Landmark

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Photogrammetry



Patient With Tracking Targets Getting Scanned

> Bone geometry from CT Scan and Skin geometry from Photogrammetry

Registered Bone and Skin Geometries



Patient 1 – Time 0 Registration





Patient 1 – 6months later Registration





Patient 2 – Time 0 Registration





Patient 2 – 6months later Registration





Rigid Registration(1)

If correct correspondences are known, one can find correct relative rotation/translation matrix directly



Rigid Registration(2)

- How to find correspondences: User input?
 Feature detection? Signatures? Landmarks?
- Alternative: assume closest points correspondence algorithm



Rigid Registration(3)

- ... and iterate to find alignment
 - Iterative Closest Points (ICP) [Besl & McKay 92]
- Converges if starting position "close enough"



Natural Landmarks for Registration of Skulls through Time





A Gaussian Mixture Model of Two Components Fitted on the Skull Data





Patient 1 - Difference Map for Upper Skull





ČÅ

Patient 2 - Difference Map for Upper Skull











Natural Landmarks for Registration of Jaws through Time





Patient 1 - Difference Map for Jaws





Patient 2 - Difference Map for Jaws



Registration for Tracking Treatment

Table 1 The normal distribution functions [formulated as N (μ , σ)] estimated for alignment errors and temporal change, extracted from the skull and the mandible signed errors

	Mandible alignment error	Temporal change (between T1 and T2)	Skull alignment error	Temporal change (between T1 and T2)
Subject 1 (treated)	N (0.0032, 0.4444 ²)	N (1.1799, 1.2044 ²)	N (0.3772, 0.3175 ²)	N (0.3772, 1.0251 ²)
Subject 2 (control)	N (0.1510, 0.4871 ²)	N (1.7621, 1.4257 ²)	N (0.1606, 0.5205 ²)	N (2.2225, 2.1840 ²)
Subject 3 (control)	N (-0.0978, 0.4287 ²)	N (0.0562, 1.3843 ²)	N (-0.0177, 0.3289 ²)	N (0.2161, 1.4472 ²)
Subject 4 (treated)	N(-0.4517, 0.4891 ²)	N(-1.3552, 1.4725 ²)	N(-0.4768, 0.4802 ²)	N(-0.4999, 1.6201 ²)
Subject 5 (control)	N (0.0274, 0.4687 ²)	N (1.1949, 1.6749 ²)	N (0.0044, 0.2432 ²)	N (0.4418, 1.6285 ²)
Subject 6 (treated)	N (-0.1342, 0.4920 ²)	N (1.1270, 2.3895 ²)	N (-0.0273, 0.2521 ²)	N (0.5246, 1.3304 ²)

All the measures are in millimetres.



CBCT-MRI Registation





M.I. for Image Registration





M.I. for Image Registration



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Definitions of Mutual Information

- Three commonly used definitions:
 - 1) I(A,B) = H(B) H(B|A) = H(A) H(A|B)
 - Mutual information is the amount that the uncertainty in B (or A) is reduced when A (or B) is known.
 - 2) I(A,B) = H(A) + H(B) H(A,B)
 - Maximizing the mutual info is equivalent to minimizing the joint entropy (last term)
 - Advantage in using mutual info over joint entropy is it includes the individual input's entropy
 - Works better than simply joint entropy in regions of image background (low contrast) where there will be low joint entropy but this is offset by low individual entropies as well so the overall mutual information will be low



Definitions of Mutual Information

• 3)
$$I(A,B) = \sum_{a,b} p(a,b) \cdot \log\left(\frac{p(a,b)}{p(a)p(b)}\right)$$

- This definition is related to the Kullback-Leibler distance between two distributions
- Measures the dependence of the two distributions
- In image registration I(A,B) will be maximized when the images are aligned
- In feature selection choose the features that minimize I(A,B) to ensure they are not related.



Additional Definitions of Mutual Information

- Two definitions exist for normalizing Mutual information:
 - Normalized Mutual Information:

 $NMI(A,B) = \frac{H(A) + H(B)}{H(A,B)}$

Entropy Correlation Coefficient:

$$ECC(A, B) = 2 - \frac{2}{NMI(A, B)}$$



CBCT-MRI Fusion Using Mutual Information Metric





Conclusion

- Our method produces alignment results of high accuracy and can thus be employed by dentists and physicians for tracking treatment results.
- We believe that a main source of outliers in our registration method is caused by segmentation.
- Further investigations on the effects of different isosurface values of the marching cubes algorithm may result in finding optimized values for registration.
- Using Mutual Information may solve this problem

