Alignment of 3D Medical Data Using a New Geometrical Descriptor

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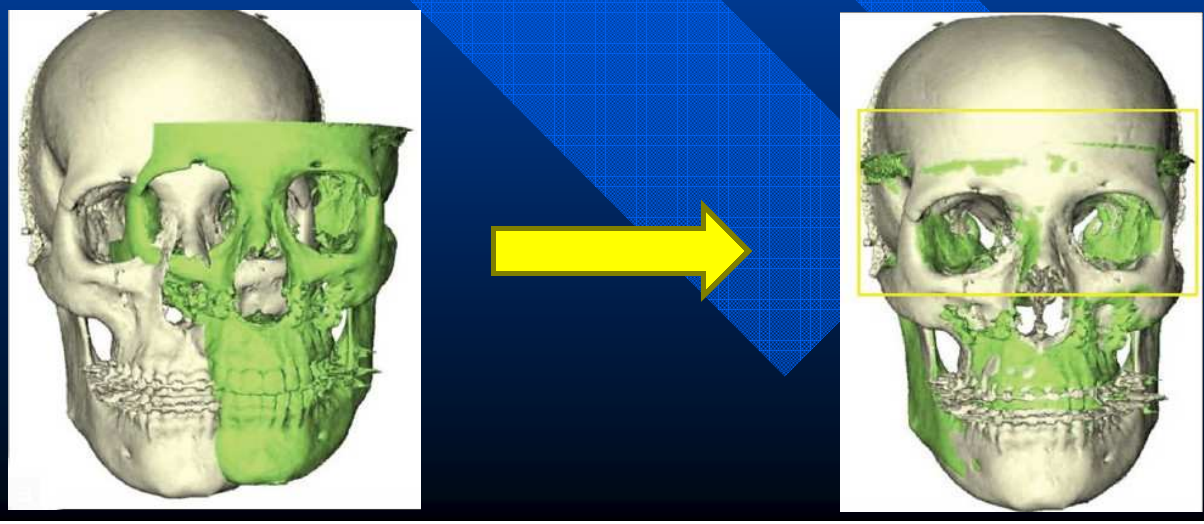
Point-based Registration

Overview

Definition:

Registration is defined as the spatial alignment of two objects. In point-based registration a limited number of points are used for aligning the objects



Point-based Registration

Overview

- Point-based Registration
  - May utilize the color properties of the points (luminosity, contrast, etc.)
  - May utilize the geometrical properties of the points
  - Objects are modeled as point-clouds
  - Point-clouds can be down-sampled
  - Can be significantly faster than conventional intensity-based/exhaustive registration

Point-based Registration

Applications

- Computer Vision
- Pattern Recognition
- Robotics
- Motion Tracking
- Medicine

Point-based Registration

Application in Medicine

- Multi-modal registration
  » CT-CT
  » CT-MRI
  » CT-PET
- Point geometry can be used when the chromatic properties of the aligned data are incompatible (CT-MRI)
- Easy to define points of interest (landmarks)
- Conventional intensity-based registration is very slow in 3D medical data

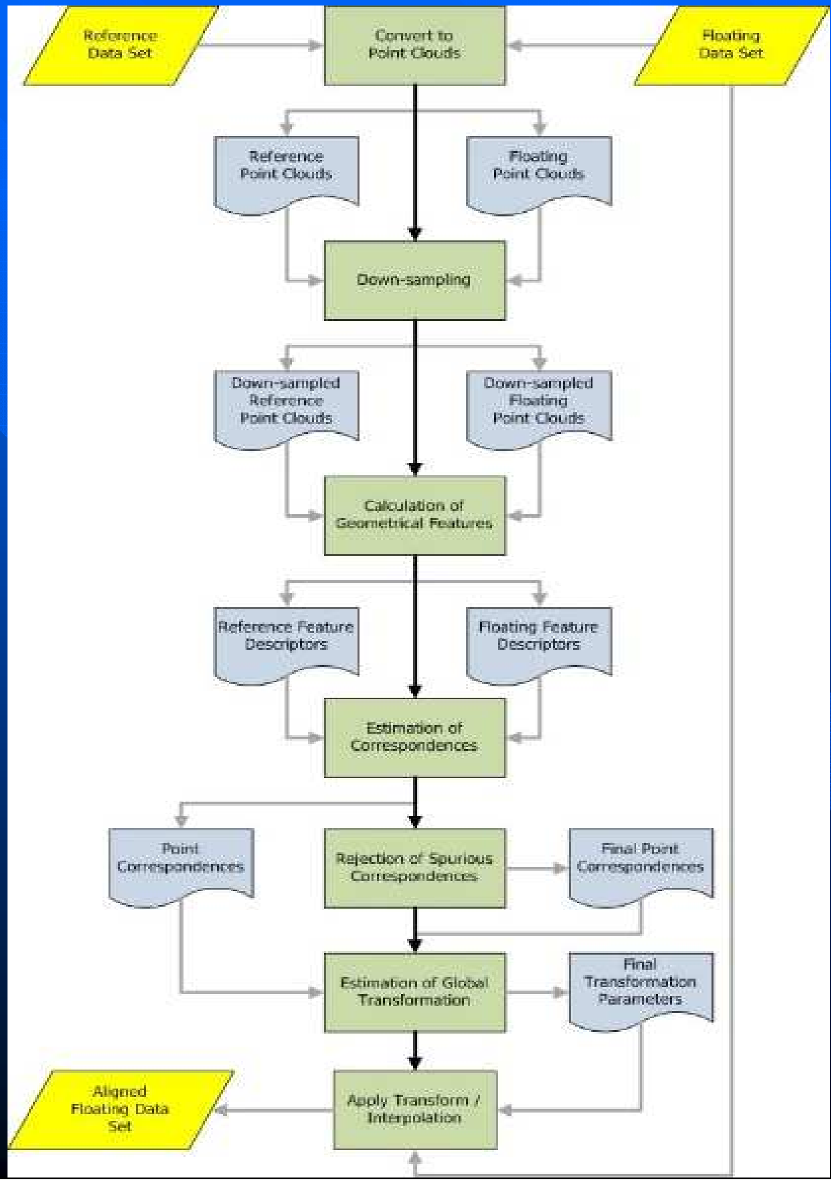
Point-based Registration

Methodology

- Convert original medical data to point clouds
- Down-sample point clouds
- Calculate geometrical descriptors
- Find corresponding points
- Estimate global transformation
- Apply global transformation directly to the original medical data

Point-based Registration

Methodology



Registration Based on Spectral Features

Overview

- Convert DICOM data to 3D point clouds
- Down-sample point clouds using 3D Harris operator
- Use Spectral Features to uniquely identify points in a point cloud
- Find corresponding points by matching Spectral Features
- Estimate global transformation from the best correspondences

Spectral Features Descriptor

Overview

- Process local scatter matrix using eigenvalue decomposition
- The results of this processing are binned into histograms
- Spectral Features can be used for finding corresponding points between two point-clouds

Spectral Features Descriptor

- Calculate local scatter matrix

$$\mathcal{S} = \sum_{p \in \mathcal{N}_p} (p - \mu)(p - \mu)^T$$

  » $p = [x, y, z]^T$

  » $\mu = \frac{1}{|\mathcal{N}_p|} \sum_{p \in \mathcal{N}_p} p$

  » $\mathcal{N}_p = \{p \in \mathbb{R}^3 : \|p - p_j\| \leq r\}$

- Calculate eigenvectors $(\widehat{e_1}, \widehat{e_2}, \widehat{e_3})$ and eigenvalues $(\lambda_1, \lambda_2, \lambda_3)$

  » Eigenvalues are sorted in descending order $(\lambda_1 \geq \lambda_2 \geq \lambda_3)$

Spectral Features Descriptor

- Define point geometry elements
  - » $\sigma_p = \lambda_3$: point-ness
  - » $\sigma_c = \lambda_2 - \lambda_3$: curve-ness
  - » $\sigma_s = \lambda_1 - \lambda_2$: surface-ness

- Define generalized spectral vector
  - » $gsv_p = \sigma_p \widehat{e_1} + \sigma_c \widehat{e_2} + \sigma_s \widehat{e_3}, \quad \forall p$
  - » $\overline{gsv}_p = \dfrac{gsv_p}{\|gsv_p\|_2}$

Spectral Features Descriptor

- Calculate quadruplet (t_1, t_2, t_3, d)

$$\vec{\delta}_2 = \vec{\delta}_1 \times \frac{p_j - p}{\|p_j - p\|}$$

$$\vec{\delta}_1 = \overline{gsv}_p$$

$$\boxed{t_1 = cos^{-1}\left(\vec{\delta}_2 \cdot \overline{gsv}_p\right)}$$

$$\boxed{t_2 = cos^{-1}\left(\vec{\delta}_1 \cdot \left[\frac{p_j - p}{\|p_j - p\|_2}\right]\right)}$$

$$\vec{\delta}_3 = \vec{\delta}_1 \times \vec{\delta}_2$$

$$\boxed{t_3 = tan^{-1}\left(\vec{\delta}_3 \cdot \overline{gsv}_{p_j}\ , \vec{\delta}_1 \cdot \overline{gsv}_{p_j}\right)}$$

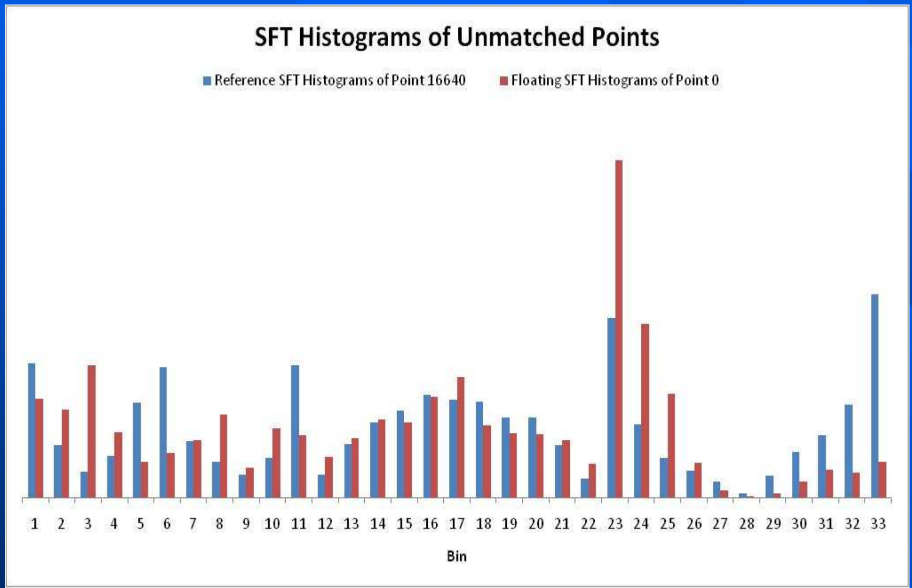
$$\boxed{d = \|p_j - p\|}$$

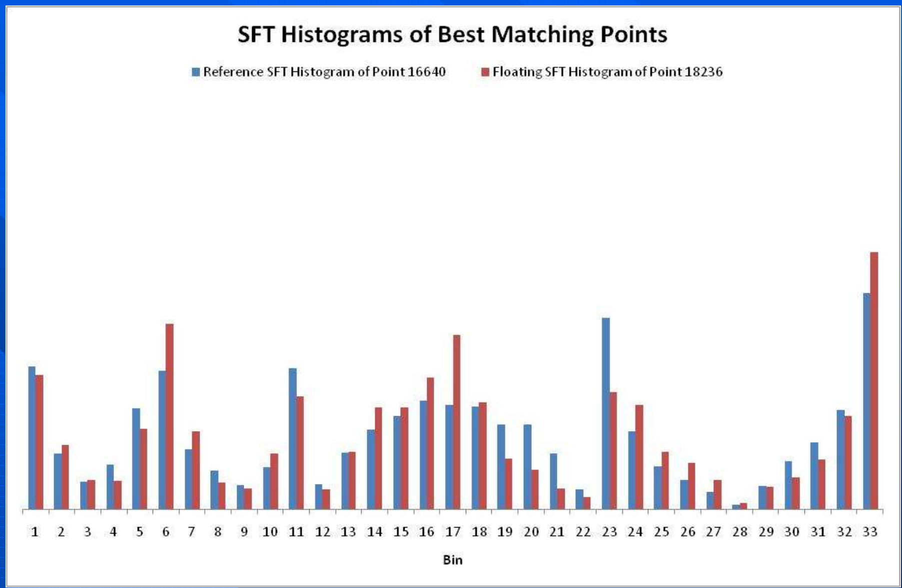
neighboring point

examined point

Spectral Features Descriptor

- Bin quadruplet into 33-bins histogram





Correspondence Estimation

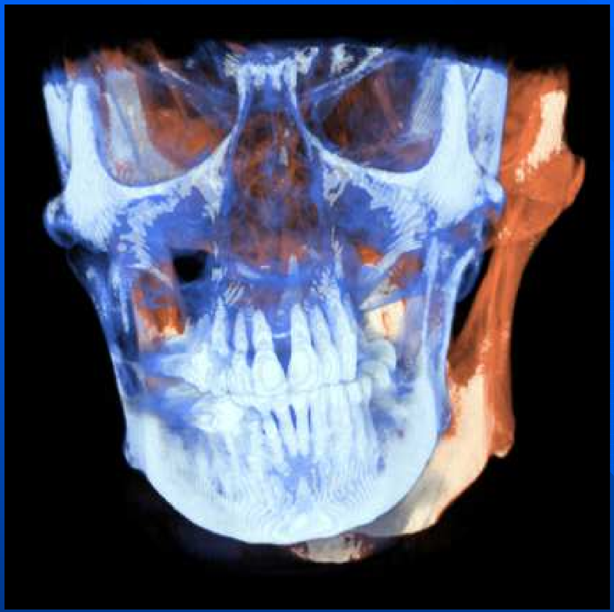
- Match histograms using k-nearest neighbor search
- Matching histograms define corresponding points
- Reject spurious correspondences using RANSAC algorithm

Registration

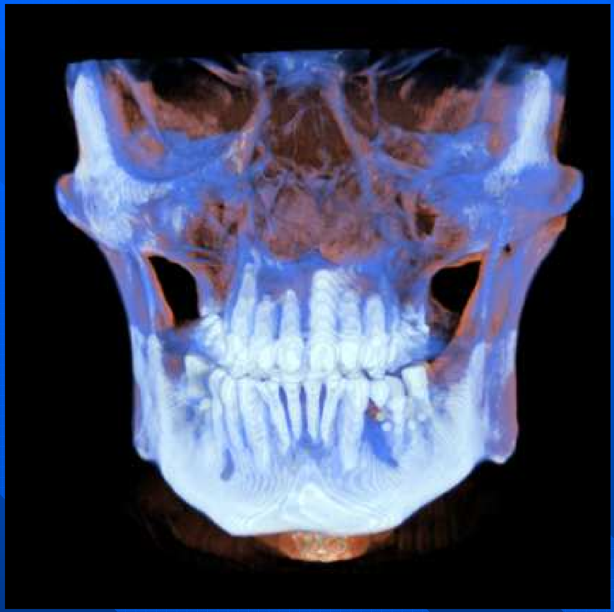
- Estimate global affine transformation through Singular Value Decomposition, on the remaining correspondences
- Apply global transformation to the original DICOM data
- Qualitative and quantitative evaluation on 20 CT volume pairs
- Compare results to Iterative Closest Point Algorithm (ICP)

Results

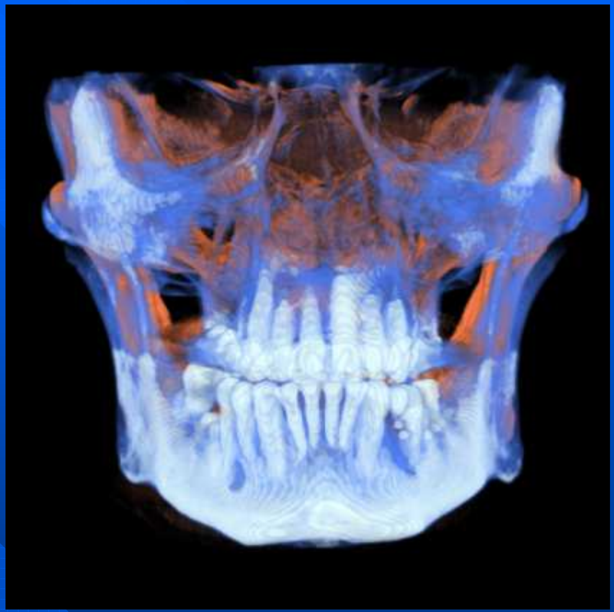
Qualitative – Fused 3D CT Volumes



Before registration



Aligned using the proposed feature descriptor



Aligned using ICP

Results

Quantitative – Correlation Coefficient

- Calculate Correlation Coefficient (CC) between the reference and the aligned CT volume

$$CC = \frac{N\sum_{\vec{r}} I_R(x,y,z) I_F(x,y,z) - \sum_{\vec{r}} I_R(x,y,z) \sum_{\vec{r}} I_F(x,y,z)}{\sqrt{N\sum_{\vec{r}} I_R^2(x,y,z) - \left(\sum_{\vec{r}} I_R(x,y,z)\right)^2} \sqrt{N\sum_{\vec{r}} I_F^2(x,y,z) - \left(\sum_{\vec{r}} I_F(x,y,z)\right)^2}}$$

Results

Quantitative – Correlation Coefficient

Pair	Methodology	
	Spectral Features	ICP
1	0.766	0.686
2	0.792	0.786
3	0.818	0.755
4	0.906	0.862
5	0.843	0.762
6	0.895	0.859
7	0.941	0.909
8	0.857	0.817
9	0.796	0.777
10	0.856	0.815
11	0.893	0.831
12	0.878	0.846
13	0.923	0.880
14	0.893	0.764
15	0.836	0.731
16	0.929	0.796
17	0.837	0.754
18	0.867	0.817
19	0.827	0.667
20	0.939	0.867
$\mu \pm \sigma$	**0.865 ± 0.051**	**0.799 ± 0.064**

Evaluation

- Registration based on Spectral Features is fast
  - » ~1 minute on average
  - » ICP required ~15 minutes on average on the same data pairs
- Registration accuracy is not hindered
- Registration does not depend on pixel intensity
  - » Ideal for aligning data from different modalities

Thank You!