Utilising Deep Learning Models for the Surface Registration Problem in HoloNav

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1. Background

- **Conventional surgical navigation systems** come with **challenges** such as the data being presented on a display
- The surgeon therefore has to continuously **switch focus** between the **surgical site** and the **screen**.
- By utilising **AR systems** such as **HoloLens 2** hand-eye coordination of the surgeon could be improved. [1]
- For HoloNav to function, it needs to be able to **register virtual data** on the **real world**
- Existing work in **AR systems** for **surgical navigation** utilise **manual registration** [2] or **landmark-based registration** [3]
- **Landmark-based registration** may not be possible due to the difficulties in marking **fiducial points** on a patient
- **Surface based registration** techniques may be used instead of landmarks, by utilising an **algorithmic approach**, or **Deep Learning models**.

2. Research Question

Can Deep-Learning methods improve the patient-alignment registration for the HoloLens?

1. **What kind** of Deep Learning methods could be trained for usage in patient-alignment registration?
2. **How would** Deep Learning models be suitable for patient-alignment registration in terms of **alignment accuracy** on a test set?
3. **How would** Deep Learning models be suitable for patient-alignment registration in terms of **time for evaluation**?
4. **Why would** Deep-Learning based approaches be used for patient-alignment registration as opposed to using **traditional algorithmic-based approaches**?

3. Method

- **Acquire** and **configure Deep Learning models** for **Point Cloud Registration** in **HoloNav**
  - RPMNet [4]
  - Overlap PREDATOR [5]
- **Train** and **evaluate** acquired **DL models** on various types of **data**:
  - Train on **ModelNet40**, test on **ModelNet40**
  - Train on **ModelNet40**, test on **HoloNav Pre-Operative Model**
  - Train and test on **Pre-Operative Model** and **Navigator Data**
- Evaluate **alignment accuracy** and **evaluation duration** on test dataset (Figure 1)
  - Isotropic **translational error**
  - Isotropic **rotational error**
  - **Chamfer Distance Error**
- Compare **evaluation results** with an **algorithmic approach**
  - Evaluate **HoloNav Pre-Operative Model** from method outlined by Weyns[6]

$$Error(Rot) = \angle R_{pred} R_{init}$$

$$Error(Trans) = ||T_{pred} + T_{init}||_2$$

$$\bar{C}D(\mathbf{X}, \mathbf{Y}) = \frac{1}{|\mathbf{Y}|} \sum_{\mathbf{y} \in \mathbf{Y}} \min_{\mathbf{x} \in \mathbf{X}} ||\mathbf{x} - \mathbf{y}||^2$$

Figure 1: The evaluation metrics utilised for RPMNet and PREDATOR.

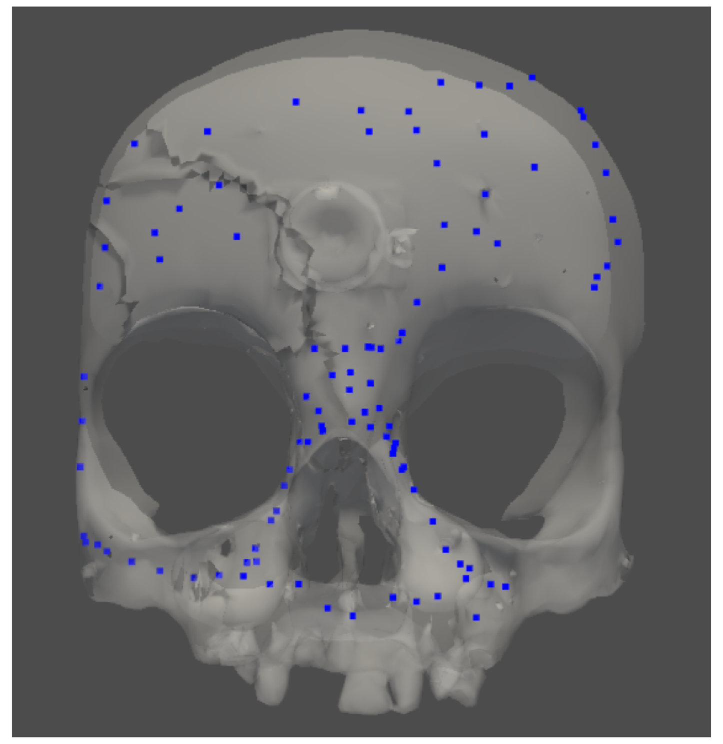

Figure 2: Visualisation of an accurate match acquired with fuducial points.

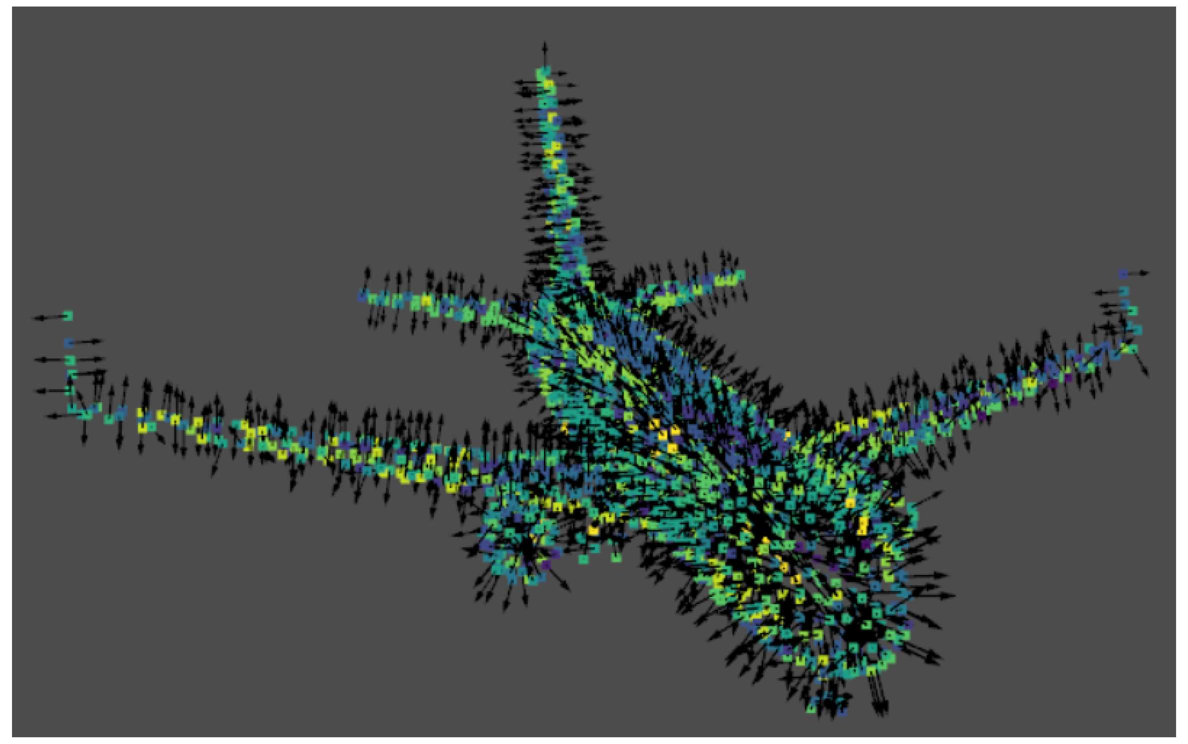

Figure 3: Visualisation of a Point Cloud data from the ModelNet40 dataset, acquired from ply_data_test.h5, index 1.

4. Results

Pre-Op Model	Navigator	Isotropic Rotation Error	Isotropic Translation Error	Modified Chamfer Distance
1	1	9.450	231.4	38.30
1	2	19.63	459.6	44.74
1	3	3.956	108.1	41.30
1	4	16.09	377.5	64.10
1	5	4.690	65.81	49.56
2	1	23.01	657.6	48.22
2	2	4.994	84.01	46.52
2	3	13.89	397.0	52.65
3	1	14.77	480.7	35.16
3	2	11.90	333.2	13.32
3	3	3.566	112.5	20.15

Figure 4: RPMNet Evaluation Results for HoloNav Pre-Op with Navigator Data

Isotropic Rotation Error	Isotropic Translation Error	Chamfer Distance
52.0718	0.0341	1288235
37.3291	0.1149	1241043
31.6535	493.0022	423.4916
0.074	**0.7065**	**10.7983**
71.3116	0.0814	2308491

Figure 5: PREDATOR Evaluation Results for HoloNav Pre-Op data

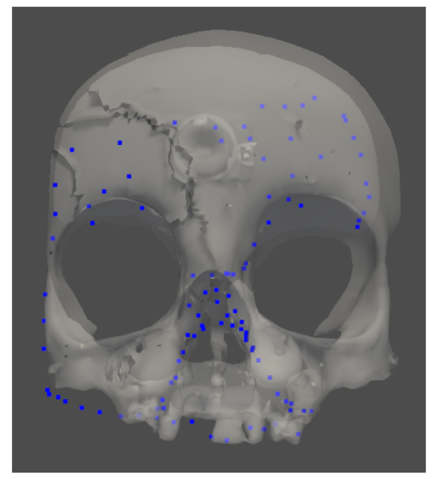

Figure 6: Visualiser Output for Model 3, Navigator Data 2

Voxel Size	RPMNet CD	FPFH Only	FPFH (With ICP)
4	4.75	519.7783	382.8319
5	16.0	150.9141	**1.00298**
6	10.6	186.9544	**1.83306**
7	11.2	**1.09607**	**1.23063**
8	7.37	7845.365	7887.997
9	6.79	109.4227	**1.09453**
10	47.6	2071.387	2109.046

Figure 7: Comparison of RPMNet accuracy to an algorithmic approach

5. Conclusion

- RPMNet demonstrates **consistent and semi-accurate matches** on **Pre-Op Data.**
- PREDATOR demonstrates **inconsistent but precise** match accuracy on **Pre-Op Data.**
- RPMNet is able to perform **general alignment** on navigator data, and provides comparable results to algorithmic approaches.
- Both models demonstrate quick evaluation times of **1.06 seconds** for PREDATOR and **1.87 seconds** for RPMNet.
- DL models can improve patient-alignment registration if **sampled points are of similar density** to Pre-Op data, or if the DL model is **configured to register uneven densities.**

References

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