Image-based registration for a neurosurgical robot: comparison using iterative closest point and coherent point drift algorithms

Cutter, Jennifer R; Styles, Iain; Leonardis, Ales; Dehghani, Hamid

DOI:
10.1016/j.procs.2016.07.006

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 90 (2016) 28 – 34

Procedia Computer Science

International Conference On Medical Imaging Understanding and Analysis 2016, MIUA 2016, 6-8 July 2016, Loughborough, UK

Image-based registration for a neurosurgical robot: comparison using iterative closest point and coherent point drift algorithms

Jennifer R. Cutter[a,b], Iain B. Styles[a,b], Aleš Leonardis[b], Hamid Dehghani[a,b,]*

[a]*PSIBS Doctoral Training Centre, University of Birmingham, Edgbaston, Birmingham, B15 2TT*
[b]*School of Computer Science, University of Birmingham, Edgbaston, Birmingham, B15 2TT*

Abstract

Stereotactic neurosurgical robots allow quick, accurate location of small targets within the brain, relying on accurate registration of pre-operative MRI/CT images with patient and robot coordinate systems during surgery. Fiducial markers or a stereotactic frame are used as registration landmarks; the patient's head is fixed in position throughout surgery. An image-based system could be quicker and less invasive, allowing the head to be moved during surgery to give greater ease of access, but would be required to retain a surgical precision of ~1mm at the target point.
We compare two registration algorithms, iterative closest point (ICP) and coherent point drift (CPD), by registering ideal point clouds taken from MRI data with re-meshed, noisy and smoothed versions. We find that ICP generally gives better and more consistent registration accuracy for the region of interest than CPD, with a best RMS distance of 0.884±0.050 mm between aligned point clouds, as compared to 0.995±0.170 mm or worse for CPD.

Peer-review under responsibility of the Organizing Committee of MIUA 2016

Keywords: Registration; ICP; CPD; neurosurgery; robot;

1. Introduction

Stereotactic neurosurgery allows procedures such as biopsy[1], neuroendoscopy[2] and electroencephalography[3] to be performed accurately and minimally invasively. Use of a stereotactic robot can improve speed and accuracy by

* Corresponding author. Tel.: +44 (0)121-414-8728; fax: +44 (0)121-414-4281.
E-mail address: h.dehghani@cs.bham.ac.uk

Peer-review under responsibility of the Organizing Committee of MIUA 2016
doi:10.1016/j.procs.2016.07.006

removing the need to manually locate the required entry point and direction for each action on the patient's head; for this, accurate registration between the patient, robot, and preoperative images is needed. A stereotactic frame or fiducial markers[4] can provide physical landmarks for preoperative registration; the frame also keeps the patient's head in place throughout the surgical procedure[5]. However, if registration could be performed quickly and accurately using a simple, image-based technique such as 3D surface capture, it would allow the head to be moved during surgery to a more convenient position and re-registered, allowing the surgical plan to be adjusted accordingly. The lack of features in the proposed imaging area (the back and top of the head) makes the problem more difficult.

1.1. Comparing registration methods

Two popular methods of point cloud registration are the iterative closest point (ICP) and coherent point drift (CPD) algorithms. ICP[6] works by pairing each point in the 'source' point cloud (the one which is to be transformed) with the nearest point in the 'reference' point cloud (points in the reference cloud can be paired to more than one source cloud point), then estimating the transformation that will most reduce the mean square of the distances between pairs. The points are then re-paired; the process is repeated until the stopping conditions are met.

Coherent point drift (CPD)[7] treats registration as a probability density estimation problem, in which one point cloud is treated as the probability distribution of the centroids of a Gaussian mixture model, and the other as data points drawn from the distribution; registration is then performed by finding the position at which the probability of the data points being observed is maximised. Motion coherence of the centroids is imposed to preserve topological structure. Myronenko and Song (2010)[8] tested CPD on example point clouds and showed it to be more accurate and robust to noise and outliers than ICP, but the examples were not similar in shape to those considered in this paper.

During neurosurgery the patient will be draped, apart from the area being operated on, therefore we are principally interested in the accuracy of registration using surface capture images of the top and back of the head. This region has few features, which may affect the robustness of the registration algorithm. We test ICP and CPD on this region for a range of transformations, using surfaces generated from MRI data, with and without added noise and with smoothed noise.

1.2. Imaging devices and surface representation

3D surface capture images can be produced using a variety of devices, including those that make use of infrared structured light (Microsoft Kinect[9] , Intel RealSense[10]), visible structured light (Birmingham Surface Capture System[11]), and infrared time-of-flight (Microsoft Kinect v2[12]). These systems are all capable of producing a point cloud representation of a surface and could be used in the operating theatre to capture a 3D model of the head. In this work representative point clouds are produced from MRI data, in order to focus on the accuracy of the registration algorithm, not the imaging technique.

2. Methods

In this paper, we compare ICP and CPD registration methods for a predefined region of the head surface, examining the effect on registration accuracy of noise and of smoothing the noise.

2.1. Point cloud creation

In order to investigate registration methods independent of imaging technique, point clouds were extracted from the MRI data of ten healthy adult subjects using NIRFAST[13]. The 'head-top' region of interest (ROI) was defined as all points above a line between the inion and a point 2 cm above the nasion (Fig. 1). In order to create an idealised point cloud to register to the initial 'ground truth' point cloud, each ROI point cloud was re-meshed in MeshLab[14] by the following process: the outer-pointing normal was calculated for each surface point using its 100 nearest neighbours; a surface mesh for the ROI was created using the algebraic set surfaces variant of the marching cubes algorithm[15] , with a grid resolution of 1000; Poisson-disk sampling was performed to give a point cloud with approximately the same number of points as the initial point cloud (a difference of less than 0.5% in all cases).

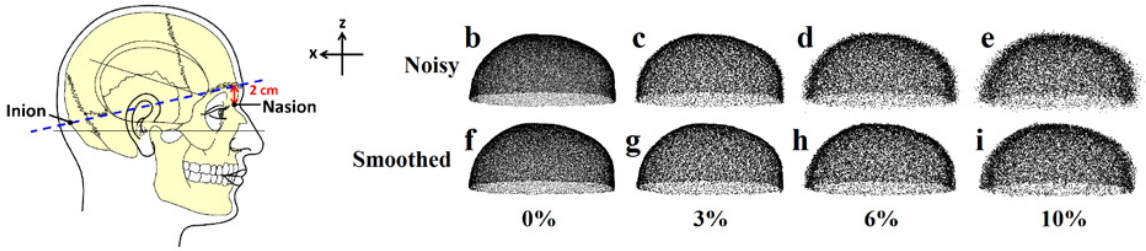

Fig. 1. (a) Skull showing inion and nasion; (b-e) Point cloud with noise added; (f-i) the same point clouds after smoothing.

2.2. Transformations

On creation, the re-meshed clouds were co-localised with the original point clouds. In order to perform registration, one of the point clouds had to be transformed to a new location. Rigid transformations (translation plus rotation) are assumed because imaging methods are available which give absolute values for the size of the object imaged, so scaling is not required. Four transformations were used to evaluate the registration methods: rotations of $\pi/40$, $\pi/20$, $\pi/10$ and $\pi/5$ radians about the x-axis, followed by translations of 2, 5, 10 and 20 mm, respectively.

2.3. Adding noise and smoothing

In order to investigate the effect of noise on registration accuracy, noise was added to the re-meshed point cloud before registration, simulating the situation in which noisy data from a 3D imaging system is registered to a preoperative MRI image. The effect of smoothing the noisy point cloud was also examined. Registration was performed in both possible directions, to determine the effect on accuracy, i.e. with the noisy or smoothed point cloud as source and the original as reference, and vice versa. Once registration is performed the calculated transformation can be reversed, to move the reference point cloud to the source, if this is more useful clinically.

In order to add the noise, the standard deviation of the point cloud in the x, y and z directions was calculated. Noise was then added to each coordinate of each point by adding a random number from a Gaussian distribution, of which the mean was zero and the standard deviation was a fixed percentage (0-10%) of the standard deviation of the point cloud in that direction (Fig. 1). Smoothing of the noisy point clouds was performed in MeshLab[14], using the 'Laplacian Smooth' filter, using three iterations, cotangent weighting and one-dimensional boundary smoothing.

2.4. Iterative Closest Point (ICP) and Coherent Point Drift (CPD) registration algorithms

ICP registration was performed using singular value decomposition to estimate the required transformation at each step of the iteration, with a maximum of 100 iterations. As an initial step, the centre of mass of the source point cloud was translated to the centre of mass of the reference point cloud.

CPD registration was performed using the MATLAB toolbox described by Myronenko and Song (2010)[8]. The fast Gauss transform option was used to compute matrix-vector products, except in instances where this produces non-finite values, where a naïve approach is used instead. A maximum of 100 iterations was used.

2.5. Registration accuracy

Registration accuracy was evaluated using the RMS distance between the point clouds after registration: for each point in the point cloud with fewer points, the nearest point in the other point cloud was found; the RMS distance between the pairs of points was used as a measure of the distance between point clouds. Where noisy or smoothed point clouds were used, the transformation calculated by the registration algorithm was applied to the original point cloud without added noise/smoothing and the RMS distance calculated using this, in order that the error measured should not be affected by the level of noise added to the point cloud. The RMS distance will not give an absolute measure of registration accuracy, but can be used to compare images from different modalities, does not depend on accurately determining the location of anatomical features, and allows consistency throughout the analysis.

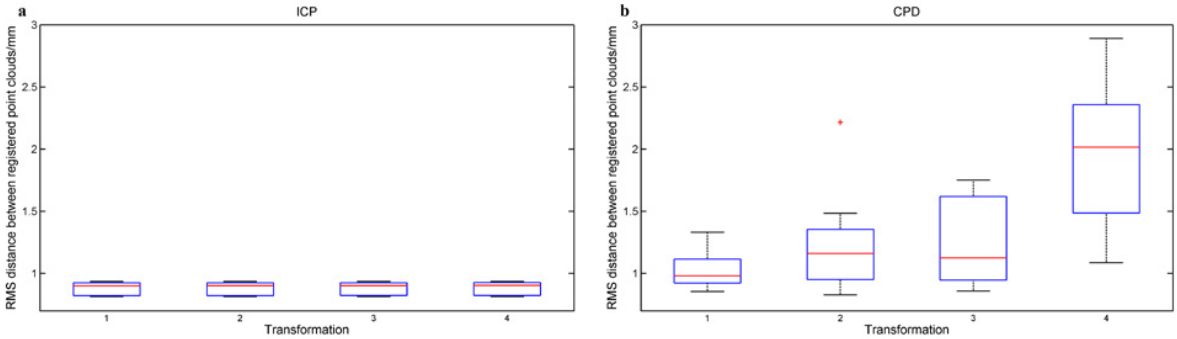

Fig. 2. RMS distances between head-tops for each transformation when registering with (a) ICP and (b) CPD.

3. Experiments and Results

We evaluated ICP and CPD for registration using re-meshed, noisy and smoothed point clouds, finding that ICP gives better registration accuracy in each case. CPD performs better when the original point cloud is used as the source (moving point cloud), but does not outperform ICP when performing the same registration with the original point cloud as the reference (stationary point cloud).

3.1. Comparison of ICP and CPD for the whole ROI, with no added noise

For each of the ten subjects, the re-meshed ROI point cloud was put through each of the four transformations described in section 2.2 and registered to the 'ground truth' ROI point cloud for that head, using both the ICP and CPD algorithms. The RMS distances between registered point clouds over the ten subjects for each transformation were found (Fig. 2). ICP gives consistently better results, which are not affected by the transformation used, whereas CPD gives a larger distance between registered point clouds with increased initial rotation and translation. The best CPD result is a mean RMS distance between point clouds of 1.03±0.14 mm for the smallest transformation, as opposed to 0.884±0.050 mm for ICP for the same transformation.

3.2. Effect of noise on registration accuracy

In order to simulate the effect of noise on registration accuracy, for each re-meshed point cloud, ten noisy point clouds were produced with 1-10% added noise, as described in section 2.3. Each was put through the four transformations described in section 2.2, and registered to the ground truth (original point cloud) using ICP and CPD. Registration was also performed in the opposite direction, by transforming the ground truth, as above, and

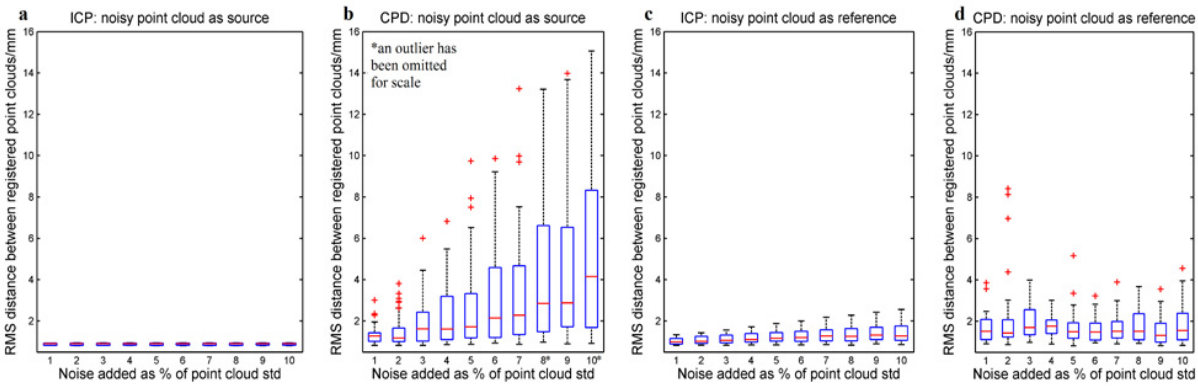

Fig. 3. Registration accuracy: noisy point cloud as source using (a) ICP and (b) CPD; as reference using (c) ICP and (d) CPD.

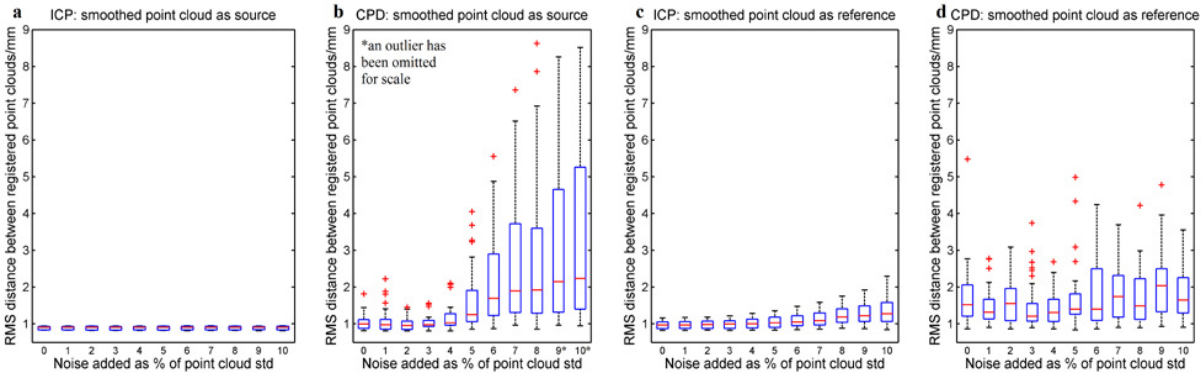

Fig. 4. Registration accuracy: smoothed point cloud as source using (a) ICP and (b) CPD; as reference using (c) ICP and (d) CPD.

registering it to the noisy, re-meshed ROI point cloud.

Where the noisy point cloud was registered to the ground truth, the ICP algorithm performed significantly better than the CPD algorithm (Fig. 3). ICP gave a consistent result across the different levels of noise, with a mean RMS distance between registered point clouds of 0.887±0.049 mm over all heads and transformations. CPD performed worse with increasing noise, with a best mean RMS distance of 1.31±0.46 mm for 1% noise. Where the ground truth was transformed and registered to the noisy point cloud, the performance of the two algorithms was much more similar. ICP gave a worse performance as the level of noise increased (best mean RMS distance was 1.02±0.15 mm for 1% noise), but CPD tended to register more accurately at higher levels of noise (1.56±0.69 mm for 9% noise).

3.3. Effect of smoothed noise on registration accuracy

A smoothing filter can be applied to noisy point clouds: in order to determine whether this would improve accuracy, the registration process described in section 3.2 was repeated with smoothed versions in place of the noisy point clouds (Fig. 4). Where the smoothed heads were aligned with the ground truth, ICP performed better (RMS distance of 0.893±0.046 mm across all noise levels), with CPD generally performing worse as the level of noise increased (the minimum RMS distance was 0.995±0.170 mm for 2% noise), as with the noisy point clouds. Where the ground truth was transformed and aligned to the smoothed heads, ICP performed better than CPD on average, but accuracy decreased with increased noise. The lowest RMS distance for ICP was 0.972±0.106mm for 1% noise; for CPD it was 1.43±0.46 mm for 4% noise. CPD accuracy was more consistent and did not vary significantly with the level of noise. Smoothing the noise did not therefore produce any improvement in registration accuracy.

3.4. Effect of CPD normalisation on registration accuracy

The CPD software has an option to normalise the data before registration, transforming it to zero mean and unit variance before registration and de-normalising it afterwards. The processes in sections 3.2 and 3.3 were repeated, using this option. This gave more consistent accuracy, where the error did not vary significantly with the level of noise. The algorithm again performed better when registering the ground truth to the noisy/smoothed point cloud, with a mean RMS distance between point clouds of 1.04±0.17 mm in the noisy case and 1.05±0.19 mm in the smoothed case. This was not as good as ICP for lower levels of noise where the ground truth was used as source and not as good for any level of noise where the ground truth was used as reference.

4. Discussion

ICP performs equally well for the different transformations used when no noise is added and when a noisy or smoothed head is used as the ‘source’, or moving, point cloud. When the noisy or smoothed point cloud is used as the ‘reference’ point cloud, the RMS distance between aligned point clouds increases with the level of noise added.

Without pre-normalisation, CPD performed worse than ICP for both smoothed and noisy heads. It performed better where the unchanged ground truth was used as the source point cloud than when it was the reference cloud. With no added noise, the distance between head-tops after alignment grew worse with larger initial transformation.

Where the pre-normalisation step was used for the CPD algorithm, there was no significant variation in the distance between point clouds after alignment with the level of noise added. Where the re-meshed point cloud was the 'source' point cloud, CPD with normalization performed consistently worse than ICP. Where the unchanged ground truth was the 'source', CPD performed as well or better than ICP for the unsmoothed noisy head-tops (ICP error increased with level of noise) and better than ICP for the smoothed point clouds.

In most instances CPD has performed worse than ICP, the reverse of the results shown in Myronenko and Song (2010)[8], where the methods were tested on several point clouds (including a fish, a rabbit, a face and a left ventricle). This may be because the region of interest studied here is fairly smooth with few features, so the best aligned position may be less well defined, particularly for noisy point clouds.

Mean registration time over the ten point clouds for the largest transformation of the re-meshed head was 381.7±33.6 s for ICP, 51.1±12.4 s for CPD and 10.3±1.2 s for CPD with normalization. It would be preferable to reduce this for use in surgery, particularly for ICP.

5. Conclusion

We have shown that for the purposes of registering our particular region of interest, ICP is generally more accurate than CPD, giving a best accuracy of RMS distance of 0.884±0.050 mm between point clouds after alignment. ICP is more effective when the original point cloud is used as reference and the re-meshed/noisy/smoothed point cloud as the source. ICP performance was not affected by adding Gaussian noise with a standard deviation of up to 10% of the standard deviation of the point cloud. Smoothing the noise using a Laplacian filter did not improve ICP registration accuracy, but did have some effect on CPD accuracy. Future work will include assessing the error at the target point based on RMS distance.

Acknowledgements

JRC gratefully acknowledges financial support from the EPSRC through a studentship from the PSIBS Doctoral Training Centre (EP/F50053X/1) and thanks Xue Wu for her help with extracting the point clouds.

References

1. Haegelen C, Touzet G, Reyns N, Maurage CA, Ayachi M, Blond S. Stereotactic robot-guided biopsies of brain stem lesions: experience with 15 cases. Neurochirurgie. 2010;56:5 363-367.
2. Tirakotai W, Bozinov O, Sure U, Riegel T, Bertalanffy H, Hellwig D. The evolution of stereotactic guidance in neuroendoscopy. Child's Nervous System. 2004;20:11-12 790-795.
3. Cardinale F, Cossu M, Castana L, et al. Stereoelectroencephalography: surgical methodology, safety, and stereotactic application accuracy in 500 procedures. Neurosurgery. 2013;72:3 353-366.
4. Varma TRK, Eldridge P. Use of the NeuroMate stereotactic robot in a frameless mode for functional neurosurgery. The International Journal of Medical Robotics and Computer Assisted Surgery. 2006;2:2 107-113.
5. Li QH, Zamorano L, Pandya A, Perez R, Gong J, Diaz F. The application accuracy of the NeuroMate robot—A quantitative comparison with frameless and frame‐based surgical localization systems. Computer Aided Surgery. 2002;7:2 90-98.
6. Besl PJ, McKay ND. Method for registration of 3-D shapes. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1992;14:2 239-256.
7. Myronenko A, Song X, Carreira-Perpinán MA. Non-rigid point set registration: Coherent point drift. Advances in Neural Information Processing Systems. 2006; 1009-1016.
8. Myronenko A, & Song X. Point set registration: Coherent point drift. Pattern Analysis and Machine Intelligence, IEEE Transactions on. 2010;32:12 2262-2275.
9. Freedman B, Shpunt A, Machline M, Arieli Y, Inventors. Depth mapping using projected patterns. U.S. Patent No. 8,493,496, 2013.
10. Draelos M, Qiu Q, Bronstein A, Sapiro G. Intel realsense = real low cost gaze. Paper presented at: Image Processing (ICIP), 2015 IEEE International Conference on, 2015;2520-2524.

11. Basevi HR, Guggenheim JA, Dehghani H, Styles IB. Simultaneous multiple view high resolution surface geometry acquisition using structured light and mirrors. Optics express. 2013;21:6 7222-7239.
12. Fankhauser P, Bloesch M, Rodriguez D, Kaestner R, Hutter M, Siegwart R. Kinect v2 for mobile robot navigation: Evaluation and modeling. Paper presented at: Advanced Robotics (ICAR), 2015 International Conference on , 2015;388-394.
13. Jermyn M, Ghadyani H, Mastanduno MA, et al. Fast segmentation and high-quality three-dimensional volume mesh creation from medical images for diffuse optical tomography. Journal of biomedical optics. 2013;18:8 086007-086007.
14. Cignoni P, Callieri M, Corsini M, Dellepiane M, Ganovelli F, Ranzuglia G. Meshlab: an open-source mesh processing tool. Paper presented at: Eurographics Italian Chapter Conference, 2008;129-136.
15. Guennebaud G, Germann M, Gross M. Dynamic sampling and rendering of algebraic point set surfaces. Computer Graphics Forum. 2008;27:2 653-662.