A novel graph-based sensorless reconstruction of the probe movement for freehand 3D echography

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1. Introduction

3D echography is a challenging task and has been more and more studied nowadays. I'm studying a novel approach for the 3D registration of the images in my research since January 2015. That's why this course project can be in resonance with my work and can extend it.

2. Method

Sensorless 3D echography can be divided in 3 main steps :

1. Registration of all pair of frames using a specific feature (speckle for example) in the echographic images
2. Reconstruction of the freehand probe's movement combining the frame-pairs motion
3. 3D reconstruction of the echographic volume using the estimated movement

I focus my work on the reconstruction process and I will implement the approach of Housden *et al.* [4], more specificely the "Frame selection" part.
Why this article ? Housden *et al.* gives a good summarizing of all previous method in sensorless registration for 3D echography, and since this date they remain a reference in the domain. The difficulty of this problem is that there are errors in the motion estimations because the freehand displacement is chaotic and implies big micro-variations. So when we want to associate the motions to reconstruct the movement, there is an accumulation of the errors. That's why it's important to minimize the choice of our motions and the hypothesis of this projet is : to choose some specific motion gives better results. Housden *et al.* didn't work accurately on the selection of the best motions so I will extend their work and propose a completely new approach for the reconstruction process :

1. After retrieving all the frame-pairs motions I will estimate a quality of these motions, learning a non-linear regression : Gaussian process [6].
2. I will construct a graph with the nodes corresponding to the frame numbers, and the weights corresponding to the quality of the motion.
3. Using Dijkstra's shortest-path [2], I will generate semi-randomly many reconstructions.
4. Finally, I we will statistically average [3] all these results to improve the accuracy.

3. Experimentation

I have access to various acquisitions of rigid monotonic freehand data (mostly in the z axis). Also, I already worked on the estimation of the frame-pairs motion so my code is available and I will not modify it for this project. To validate my study, I will implement the mean target registration error introduced by De Kraats *et al.* [1] wich gives a good approximation of the registration error. I will compare my method versus Housden *et al.* using different acquisitions with the hope of better results. I will also invest the benefit of the averaging (4) versus just the shortest path (3).Finally, I plan to try the generation of a minimum spaning tree by Prim [5] and compare this with the shortest-path tree.

References

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