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Optimization Algorithms for Plane Selection in Interactive 3D Image Segmentation

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1. Background

The problem is finding the plane of highest total uncertainty in an uncertainty field.
Iterative optimization algorithms are used for this.
Finding better planes means user corrects more errors per labeled image, meaning less user input is needed.

2. Goal

The goal of this research is to find which optimization algorithm is best suited for finding the most uncertain plane in an uncertainty field.
This plane can be parameterized by the normal vector of the plane and a point on the plane.

3. Algorithms

Three algorithms were tested:

- Particle swarm optimization, which uses the cost function itself. It starts with a number of particles scattered around the solution space, whose position is updated every iteration:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_{best_i}^t - x_i^t) + c_2 r_2 (g_{best}^t - x_i^t)$$

- Gradient descent, which uses the first derivative. Here the gradient of the point and the gradient of the normal are computed separately:

$$\nabla_{p_P} U_P = \int_\infty \int_\infty \nabla_x U(f_P(u,v)) du dv$$

$$\nabla_{n_P} U_P = \int_\infty \int_\infty (u J_{a,n_P}^T + v J_{b,n_P}^T) \nabla_x U(f_P(u,v)) du dv$$

- L-BFGS-B, which approximates the second derivative. It does so by iteratively improving an approximation of the inverted Hessian matrix.

Since gradient descent and L-BFGS-B tend to find local optima instead of global optima, they are randomly initialized multiple times.

5. Results

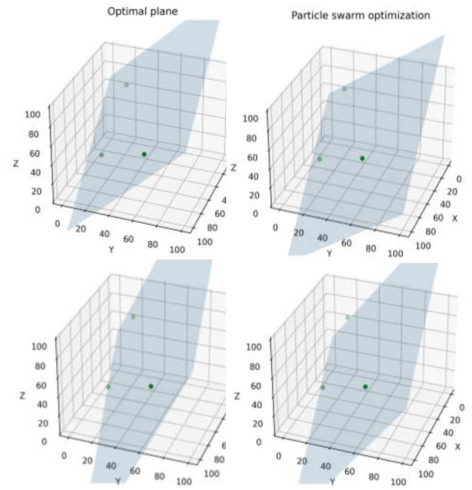

Figure 1: The optimal plane in the artificial uncertainty field, along with example of planes found by the three optimization algorithms.

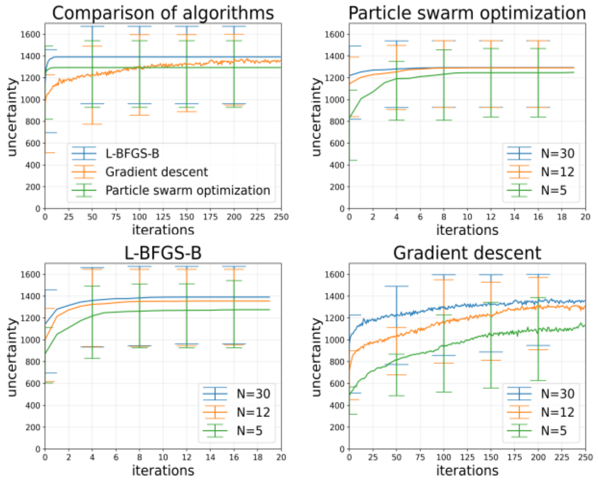

Figure 2: A comparison for the different algorithms in the top left, a comparison of different number of particles or random initializations for each algorithm in the three other graphs..

4. Experiments

These algorithms were evaluated in two experiments. The first experiment involves creating an artificial uncertainty field where the global optimum passes through three points.

The second experiment involves running the three algorithms on 24 different uncertainty fields acquired from running the pipeline for one iteration. This was done for different numbers of particles for particle swarm optimization and for different numbers of random instantiations.

6. Conclusion

Overall, L-BFGS-B seems to perform the best. Gradient descent converges much slower, while particle swarm optimization converges to lower values.

Future work includes evaluating how higher uncertainty affects the quality of the segmentation in a complete pipeline and evaluating more optimization algorithms.