Improving the Accuracy of 2D-3D Registration of Femur Bone for Bone Fracture Reduction Robot using Particle Swarm Optimization

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ABSTRACT

Population-based optimization algorithms have proved themselves very effective and efficient way for solving some complex problems, particularly for problems of non-linear and non-convex nature. 2D-3D registration is one such problem where inherent non-linearity and high-dimensionality along with non-convex optimization nature makes it very difficult to achieve satisfying accuracy, especially when starting point for optimization is not ideal. Because of the underlying structure of population-based optimization algorithms, especially particle swarm optimization (PSO), 2D-3D registration with PSO is expected to yield better accuracy compared to conventional gradient-based optimization algorithms. Another considerable factor is that gradient approximation error makes non-gradient methods more favorable for the case of 2D-3D registration over gradient-based methods. Our experiment on 2D-3D registration using virtual X-ray shows that PSO has better accuracy and convergence rate than gradient based approaches like Stochastic Gradient Descent (SGD), Momentum Stochastic Gradient Descent (MSGD) and Nesterov Accelerated Gradient (NAG).

CCS CONCEPTS

• **Theory of computation → Nonconvex optimization**;

KEYWORDS

2D-3D Registration, Particle Swarm Optimization, Non-convex Optimization

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1 INTRODUCTION

Recently, population-based optimization algorithms are getting more attention for solving non-linear and non-convex optimization problems. Particle Swarm Optimization is one of the newest members of this group of algorithm. 2D-3D registration is a problem with non-convext and non-linear nature which is enabling image-guided interventions possible for robot-assisted minimally invasive surgeries[4]. The object of 2D-3D registration is to bring pre-operative 3D data and intra-operative 2D data into a common coordinate system. Although it has been a topic of research for several decades, accuracy is still dependent on application area which makes it very hard to choose an algorithm off-the-shelf.

By far, gradient descent is the most commonly used optimization strategy for 2D-3D registration. First appearing in 1995 by Kennedy and Eberhart [2], Particle Swarm Optimization quickly became a popular optimization algorithm to solve many problems. Although it has shown very promising result, compared to other optimization algorithms, PSO is relatively untapped algorithm in 2D-3D registration area.

2D-3D registration is largely an application specific algorithm and there are not many studies on fractured femur bone registration. We implemented PSO along with three other gradient-based optimization algorithms for 2D-3D registration of femur bone fracture for bone fracture reduction robot[3]. We compared accuracy and convergence rate of PSO with traditional gradient based methods. And we found that PSO is much more effective for 2D-3D registration of fractured femur bone than other conventional gradient based methods.

2 METHODOLOGY

2.1 Gradient-based Optimization

We have used three variations of gradient-based optimization algorithm and a variation of PSO. Stochastic gradient descent (SGD) can be seen as the basic form of gradient descent optimization algorithm. Rumelhart et al. [6] introduced momentum term which makes convergence of SGD much faster and reduces oscillation around local minima. Nesterov Accelerated Gradient (NAG) [5] looks ahead by not calculating gradient w.r.t. current parameters but by calculating gradient w.r.t. approximate future position of parameters.

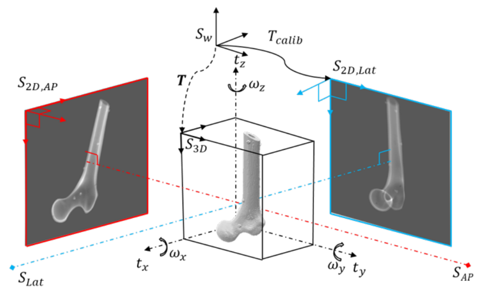

Figure 1: Geometrical setup of the registration of 3D CT data to two 2D X-ray images

2.2 Particle Swarm Optimization (PSO)

PSO algorithm simulates the social behavior of a swarm. Each individual particles of the swarm can be seen as a position in solution-hyperspace and according to PSO, they tend to cluster at a position where optimum solution could be found. Each particle evaluates their current position by comparing with their own experience which is called cognitive intelligence and with globally known best position so far which is called social intelligence.

Our implementation of PSO can be described as follow.

$$\begin{cases} v_t = \omega v_{t-1} + \delta_1 \sigma_1 \times (P_i - X_{i,t-1}) + \delta_2 \sigma_2 \times (G - X_{i,t-1}) \\ X_t = X_{t-1} + v_t \end{cases} \tag{1}$$

where at iteration t, X_i is the ith particle that changes its position by a velocity vector v_t, ω is the momentum term which also implies its confidence on its current position and it is usually set to 0.9, δ_1 and δ_2 are cognitive factor which imply its confidence on its previous experience and social factor which implies its confidence on social intelligence respectively, σ_1 and σ_2 are two different uniformly distributed random numbers drawn from the range of 0 and 1, P_i is particles' previous best known position where G is the global best known position so far.

In practice, we clip velocity according to $v_i \epsilon [-v_{max}, v_{max}]$ rule to keep x_i within reasonable boundary. And also, δ_1 and δ_2 can be set by using constriction coefficient suggested by Clerc et al. [1]. We used 50 particles with maximum 75 iterations to converge.

3 EXPERIMENT

We are going to apply 2D-3D registration algorithm for femur bone fracture reduction robot. For robot-assisted surgery, alignment of broken bone parts are done using the help of the robot which has access to pre-operative 3D CT data and intra-operative 2D X-ray images. 2D-3D registration algorithm finds transformation matrix between 2D and 3D coordinate by iteratively minimizing distance between 2D X-ray images and generated DRR images from CT data. Fig. 1 illustrates the geometric setup for 2D 3D registration.

For evaluation, we used virtual X-rays in our experiment. We set our virtual bone at a specific position to get AP and Lateral DRR image. We used this DRR images as if they are 2D X-ray images in our 2D-3D registration algorithm. 3D CT data is taken pre-operatively for a broken artificial femur bone. We set our capture range to ±10mm for translation parameters and ±10° for rotation parameters and generated 20 random initial positions to evaluate the algorithms.

Table 1: Convergence Rate and Accuracy

	Translation (mm)	Rotation (°)	CR (%)
SGD	-	-	0
MSGD	0.64 ± 0.37	0.98 ± 0.52	30
NAG	0.38 ± 0.30	0.57 ± 0.47	30
PSO	0.11 ± 0.16	0.18 ± 0.29	70

Euclidean distance is used to calculate the final distance from our desired position and optimized position in space. Convergence rate is also used to evaluate our algorithms. One particular experiment is said to be converged if the final euclidean distance is less than 2mm and 2° for translation and rotation respectively. These values are set empirically with suggestions from surgeons.

4 RESULT AND DISCUSSION

Table 1 shows the comparison of convergence rate and accuracy four optimization algorithms used. SGD failed to converge withing the set threshold. MSGD and NAG both converged 30% times, but NAG produced much better accuracy than MSGD. And PSO showed the best accuracy and convergence rate among 4 different optimization algorithms.

5 CONCLUSIONS

In this paper, we showed that PSO is a very good alternative as optimization algorithm especially for femur bone registration with much better convergence rate and very good convergence accuracy than other gradient-based optimization algorithms. PSO produces 70% convergence rate and 0.11 ± 0.16mm translation accuracy and 0.18 ± 0.29° rotational accuracy.

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