Introducing Learning Rate Adaptation CMA-ES Into Rigid Intraoperative 2D/3D Registration for Spinal Surgery

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Code Repository

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INTRODUCTION

● Background

Intraoperative 2D/3D registration is a process aimed at aligning intraoperative 2D images, such as X-ray images, with corresponding preoperative CT volumes. It is a crucial step in providing surgical planning guidance and navigation positioning for spine surgeries like percutaneous vertebroplasty and pedicle screw internal fixation. The covariance matrix adaptive evolution strategy (CMAES) has been widely used in the field of 2D/3D registration in recent years. This optimization method exhibits exceptional robustness and usability for complex surgical scenarios.

● Main Challenges

However, due to the inherent ill-posed nature of the/3D registration task and the presence of numerous local minima in the landscape of similarity measures, evolution strategies often require a larger population size in each generation to ensure the stability of registration and the globality and effectiveness of search, which makes the entire process computationally expensive.

● Contribution

In this paper, we build a 2D/3D registration framework based on a learning rate adaptation CMA-ES manner (LRA-CMA). The framework employs a fixed and small population size, leading to minimized runtime and optimal utilization of computing resources. We conduct experimental comparisons between the proposed framework and other intensity-based baselines using a substantial volume of synthetic data. The results suggest that our method demonstrates superiority in both registration accuracy and running time compared with other optimization-based baselines.

● Problem Definition

The problem of rigid 2D/3d registration can be viewed as optimizing the following formula:

$$\theta = arg\max_{\bar{\theta}} \mathcal{S}(I, P(\bar{\theta}; V))$$

where I is the 2D fixed X-ray image, $\mathcal{S}(\cdot,\cdot)$ is the similarity function which is also the target object function of LRA-CMA. , and V is the 3D volume. The pose θ that needs to be estimated is a vector with six degrees of freedom $\theta = (rx, ry, rz, tx, ty, tz)$. $P(\cdot;\cdot)$ is the projection operator which uses V and pose $\bar{\theta}$ to generate DRR (the moving image).

METHODOLOGY

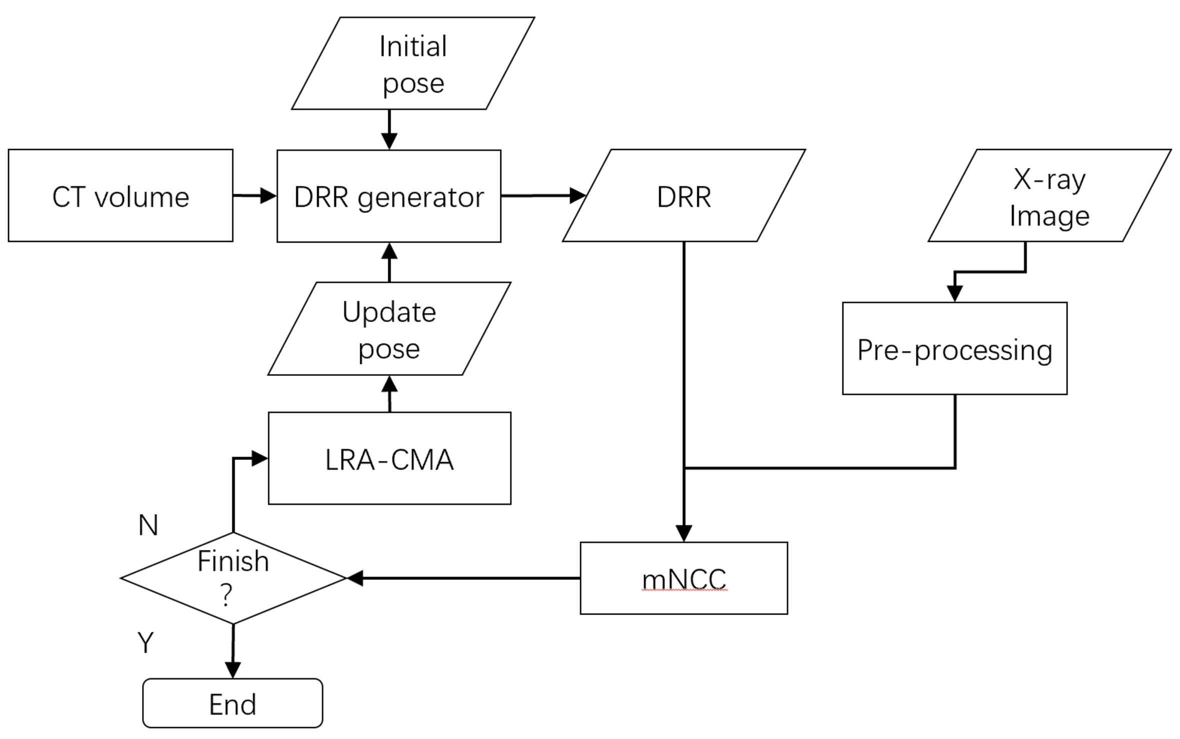

Fig.1. An overview of the 2D/3D registration framework using LRA-CMA.

● LRA-CMA:

CMA-ES uses multivariate normal distribution $N(m^{(t)}, \sigma^{(t)}\pi^{(t)} \to \Sigma^{(t)})$ to generate candidate solutions to minimize the objective function with fixed population size: $\lambda = 4 + \lfloor \ln(d) \rfloor (d = 6)$. We first use the parameter update strategy of CMA-ES to obtain $\Delta m^{(t)}$ and $\Delta\Sigma^{(t)}$, then use them to calculate the new evolutionary path and current signal-to-noise ratios $\eta_m^{(t)}$ and$\eta_\Sigma^{(t)}$.

$$m^{(t+1)} = m^{(t)} + \delta_m^{(t)} \Delta m^{(t)}$$

$$\Sigma^{(t+1)} = \Sigma^{(t)} + \delta_\Sigma^{(t)} \Delta\Sigma^{(t)}$$

Learning rate adaptation mechanism: the core step to adjust step size δ so that the signal-to-noise ratio $\eta = \alpha\delta$:

$$\delta^{(t+1)} = \delta^{(t)} \cdot \exp(\min(\gamma\delta^{(t)}, \beta) \prod_{[-1,1]} (\frac{\eta^{(t)}}{\alpha\delta^{(t)}}))$$

where α, β and $\gamma \in \mathbb{R}$ are hyperparameters. In addition, in order to ensure that the optimal σ is maintained after η changes, a step-size correction strategy is adopted

$$\sigma^{(t+1)} = \frac{\delta_m^{(t)}}{\delta_m^{(t+1)}} \sigma^{(t+1)}$$

● Similarity Function:

$$mNCC(I, I_m) = (1 - \mu) NCC(I, I_m) + \mu \sum_{P(p_i, p_j) \in \Omega_K} LNCC(I, I_m, p_i, p_j, r)$$

where NCC is the normalized cross-correlation, LNCC is the patch-based NCC and μ is a hyperparameter from (0, 1). The patches we use are squares with radius r and center point $(\boldsymbol{p_i}, \boldsymbol{p_j})$.

QR code for the LRA-CMA algorithm

RESULTS

The dataset consists of 52 CT scans from VerSe [10]. We resampled the CT images to an isotropic spacing of 1.0 mm and cropped or padded each dimension to obtain 256 × 256 × 256 volumes with the spine ROI approximately in the center. We selected 5 scans for hyperparameter tuning and 47 scans were used for testing. We defined the intrinsic parameter of the X-ray simulation environment as a Perlove PLX118F C-Arm. The images were down-sampled to have dimensions of 256 × 256 with a pixel spacing of 0.798 mm/pixel. For testing, we use 1000simulated X-ray images with angles of U (-20, 20) degrees in three directions, with translation in mm of U (-30, 30) for in-plane (X and Y) direction and U (-50, 50) for depth (Z) direction. The volume V we use is segmented through the mask provided by the dataset to reduce the impact of soft tissue on the image quality of DRRs.

Table 1. 2D/3D registration performance comparing with the baseline methods. The evaluation includes measuring the mean, standard deviation, and median of the mean target registration error (mTRE), as well as the pose error (in degree and mm) and registration time (in seconds).

Method	mTRE(mm)↓		Pose error↓		Reg.
	mean(std)	median	Rot.	Trans.	time
Initial	259.2(116.8)	250.5	33.3	60.1	N/A
CMA-ES	171.8(87.4)	168.0	**24.1**	72.7	50.6
GD	202.5(134.4)	175.0	26.9	**49.3**	28.3
LRA-CMA(gc)	186.8(105.7)	171.5	25.9	54.9	20.7
LRA-CMA	**169.4(92.6)**	**158.6**	24.4	55.9	**20.5**

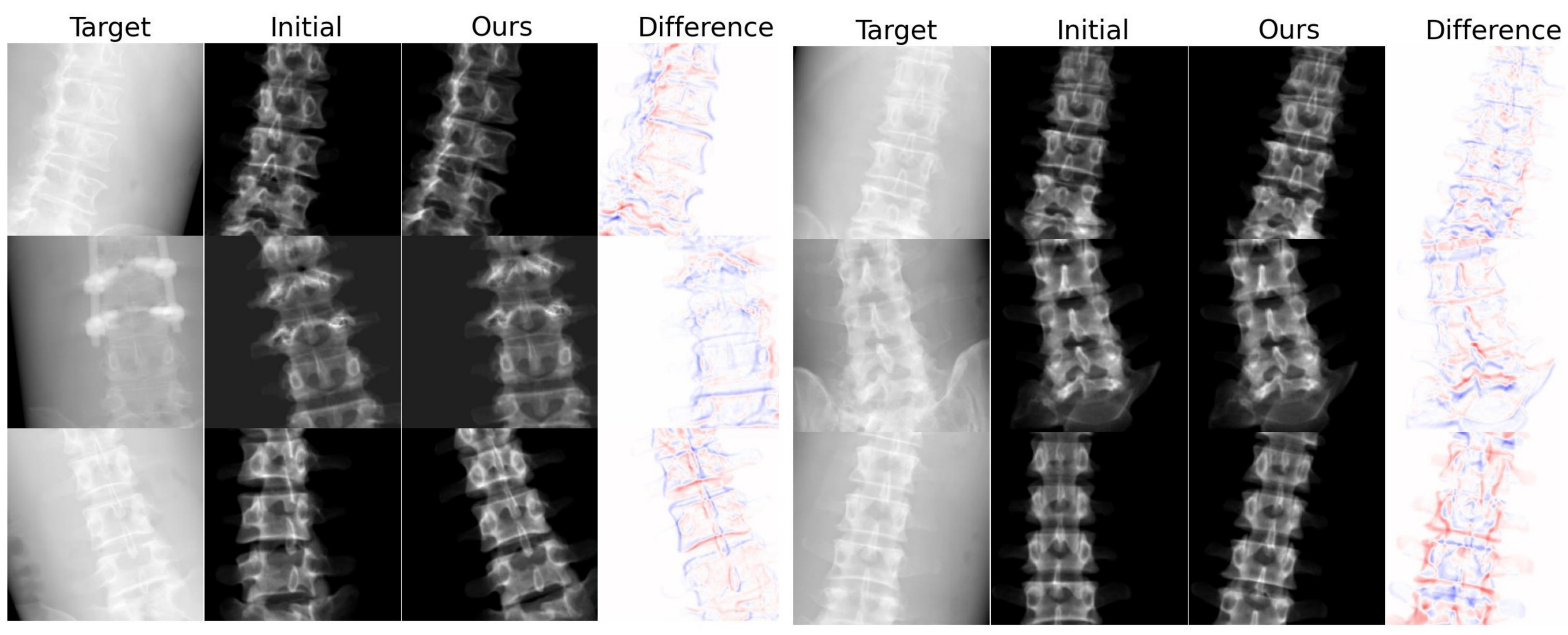

Fig. 2. Qualitative results of the proposed framework. In columns 1&5 are the preprocessed target images; in columns 2&6 and 3&7 are the DRRs corresponding to the initial pose and the registration pose of our method respectively; the difference maps between the estimated poses and the ground truth are shown in columns 4&8.

By comparing with other existing intensity-based benchmarks, the registration method using LRA-CMA as the optimizer has less running time and higher registration accuracy. Future work will focus on vectorization and parallel processing on GPU to maximize the use of computing resources and reduce the running time, as well as adjusting current hyperparameter settings to further improve the registration performance of the framework.

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