Observation-Driven Adaptive Differential Evolution for Robust Bronchoscope 3-D Motion Tracking

Xiongbiao Luo and Kensaku Mori

Information and Communications Headquarters, Nagoya University

Abstract. This paper proposes an observation-driven adaptive differential evolution (OADE) algorithm for accurate and robust bronchoscope 3-dimensional (3-D) motion tracking during electromagnetically navigated bronchoscopy. Two advantages of our framework are distinguished from any other adaptive differential evolution methods: (1) current observation information including sensor measurement and video image is used in the mutation equation and the selection function, respectively, and (2) the mutation factors and crossover rate are adaptively determined in terms of current image information. From experimental results, our OADE method was demonstrated to be an effective and promising tracking scheme. Our approach can reduce the tracking position error from 3.9 to 2.8 mm, as well as the position smoothness from 4.2 to 1.4 mm.

1 Introduction

During bronchoscopy navigation, bronchoscope 3-D motion tracking still remains a challenge to find the camera motion parameters in the reference coordinate system and can be considered as a 6-degree-of-freedom (DOF) optimization problem. To estimate the bronchoscope movement, two major methods (or a combination of them) were published: (1) intensity-based image registration: constructing an optimization function to minimize the pixel difference between real video images and virtual renderings generated from pre-operative images (e.g., CT) [1234]; and (2) electromagnetic tracker (EMT): fixing a sensor at the bronchoscope tip and directly measuring its motion [5678]. Image-based methods work well but suffer from image artifacts (e.g., motion blurring) and easily get trapped in local minima during optimization. Although the EMT-based approaches have been commercialized to clinical applications [9], their tracking accuracies are deteriorated by respiratory motion and magnetic field distortion.

This paper seeks for a more robust and accurate tracking framework to boost the EMT approaches to meet clinical requirements. As one of powerful evolutionary algorithms, differential evolution (DE), which was developed by Storn and Price [10], has been applied as a successful optimization technique to address any complex problems [11]. However, its performance reckons on evolutionary parameters of the mutation factor and the crossover rate. We modified such an algorithm and proposed an observation-driven adaptive differential evolution...
(OADE) method, which can not only adaptively determine the evolutionary parameters based on intensity information but also add observation information of the EMT sensor and video image to mutate each individual in a population.

The main contribution of this work is summarized as follows. First, we modified the mutation equation in the DE algorithm by integrating current observation information, which can control the perturbation velocity and direction of each individual during evolution, augmenting the DE performance. Next, to the best of our knowledge, our OADE framework is a novel application of DE in bronchoscope 3-D motion tracking. We successfully formulated bronchoscope 3-D motion tracking as an OADE-based stochastic optimization process. EMT sensor measurements and bronchoscopic video images can be effectively led into OADE to achieve a more robust and accurate tracking method. Additionally, our OADE framework can be suitable to track other endoscope, e.g., colonoscope.

2 Differential Evolution

2.1 Operations of DE

Basically, the DE method propagates a population of individuals or vectors \( \{X_{i,G}|X_{i,G} \in \mathbb{R}^D\}_{i=1}^N \) (\( N \) is the population size, \( G \) is the generation index, and \( D \) is the dimension of vector) toward to the global optimum during any stochastic optimization procedures. After initializing the parameters of the population \( \{X_{i,G}|X_{i,G} \in \mathbb{R}^D\}_{i=1}^N \), each target vector or individual \( X_{i,G} \), which is considered as a potential solution to a multi-dimensional optimization problem, will be evolved by performing three operations, as discussed as follows.

**Mutation.** For target vector \( X_{i,G} \) at generation \( G \), its mutant vector \( V_{i,G} \) can be obtained by several frequently used mutation schemes in DEs [11]:

\[
V_{i,G} = \begin{cases} 
X_{r_1^1,G} + F_i \left( X_{r_2^1,G} - X_{r_3^1,G} \right) & (1) \\
X_{\text{best},G} + F_i \left( X_{r_1^1,G} - X_{r_2^1,G} \right) & (2) \\
X_{i,G} + F_i \left( X_{\text{best},G} - X_{i,G} \right) + F_i \left( X_{r_1^2,G} - X_{r_2^2,G} \right) & (3) \\
X_{\text{best},G} + F_i \left( X_{r_1^3,G} - X_{r_2^3,G} \right) + F_i \left( X_{r_3^3,G} - X_{r_4^3,G} \right) & (4) \\
X_{r_1^4,G} + F_i \left( X_{r_2^4,G} - X_{r_3^4,G} \right) + F_i \left( X_{r_4^4,G} - X_{r_5^4,G} \right) & (5) 
\end{cases}
\]

which corresponds to \( 1 \sim 5 \) mutation strategies of “DE/rand/1”, “DE/best/1”, “DE/target-to-best/1”, “DE/rand/2”, and “DE/best/2”, respectively; these strategies are consistent with a general name or convention: \( DE/a/b \), where \( DE \) denotes the standard DE algorithm, \( a \) indicates the base vector to be perturbed, and \( b \) is the number of difference vectors. The indexes \( r_1^1, r_2^1, r_3^3, r_4^4, \text{ and } r_5^5 \) are mutually exclusive integers chosen randomly from set \( \{1, \ldots, i-1, i+1, \ldots, N\} \). The part \( (X_{r_1^1,G} - X_{r_2^1,G}) \) in Eq. 1 represents the difference vector, \( X_{\text{best},G} \) is the best individual at generation \( G \), and \( F_i \) is the mutation factor.

**Crossover.** After mutation, a binomial crossover operation is performed to generate trial vector \( U_{i,G} = \{u_{i,G}^1, \ldots, u_{i,G}^D\} \) in accordance with target vector \( X_{i,G} = \{x_{i,G}^1, \ldots, x_{i,G}^D\} \) and mutant vector \( V_{i,G} = \{v_{i,G}^1, \ldots, v_{i,G}^D\} \):