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A finite-time particle swarm optimization algorithm for odor source localization ☆

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ABSTRACT

This paper is concerned with a finite-time particle swarm optimization algorithm for odor source localization. First, a continuous-time finite-time particle swarm optimization (FPSO) algorithm is developed based on the continuous-time model of the particle swarm optimization (PSO) algorithm. Since the introduction of a nonlinear damping item, the proposed continuous-time FPSO algorithm can converge over a finite-time interval. Furthermore, in order to enhance its exploration capability, a tuning parameter is introduced into the proposed continuous-time FPSO algorithm. The algorithm's finite-time convergence is analyzed by using the Lyapunov approach. Second, the discrete-time FPSO algorithm is obtained by using a given dicretization scheme. The corresponding convergence condition is derived by using a linear matrix inequality (LMI) approach. Finally, the features and performance of the proposed FPSO algorithm are illustrated by using two ill-posed functions and twenty-five benchmark functions, respectively. In numerical simulation results, the problem of odor source localization is presented to validate the effectiveness of the proposed FPSO algorithm.

1. Introduction

This paper is motivated by our collaborations with an environmental protection institute in order to reduce the localization time of the dangerous gas source based on a cooperative multi-robot system, which can be formulated as the problem of odor source localization. In the light of the studies [12,34], this problem is an ill-posed and dynamical optimization problem [11,16,41,35,29], and its main characteristics can be summarized as

- The maximum odor concentration occurs in the vicinity of the position of the odor source and there exist multiple local odor concentration maxima along the plume.
- The positions of local concentration maxima change with time and the local odor concentration maxima are also time-varying.
- The odor concentration can be only detected within the plume except which the odor concentration approaches to zero.

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On the basis of the characteristics of the odor source localization problem, the PSO algorithm and its variants, such as PSO [30], CPSO [19], PPSO-IM [25], and LPSO [27], which have the attribute of the "decision and control mechanism" [22–24], can been used to make a decision on the positions of the odor source and to control the robots to move toward the positions. It is worth mentioning that the aforementioned approaches focus on how to design a new decision algorithm to make a decision on the probable position of the odor source in terms of concentration information and wind information detected by the robot group. However, cooperative control algorithms, which can control the robot to reach the predicted position of the odor source, have not paid enough attention in the existing literature.

In fact, cooperative control algorithms are significant in the problem of odor source localization. From the control engineering point of view, since the robots are used to search for the odor source, a cooperative controller should be of the better performance in disturbance rejection and the robustness against uncertainties. Moreover, since the predicted position of the odor source is time-varying, the cooperative controller should be of the better tracking performance. Due to the characteristics of the odor source localization problem, in order to adapt the dynamical search environment, the cooperative controller should enable the system to be stable over a finite-time interval. Furthermore, the knowledge about the dynamical search environment is only from the current and previous information of the robot group. As a consequence, the robot is required to quickly move to the predicted position of the odor source such that new information can be obtained to update the predicted position of the odor source [40]. Because of several advantages including higher control accuracy, better disturbance rejection, and robustness against uncertainties [4], finite-time controller design has received a growing interest from researchers and engineers [9,43]. In order to meet the aforementioned requirements, it is of practical significance to develop a finite-time cooperative controller, which is in conjunction with the decision algorithm, to form an FPSO algorithm, which is the motivation of the current study.

Notice that the FPSO algorithm can be regarded as a more generalized form of the PSO algorithm. It can be used to control the real robot group. It can also be viewed as an example such that researchers can separately design the decision algorithm and the control algorithm in terms of the characteristics of the optimization problem. The partial version of this paper appears in [26]. In this paper, first, we will propose a continuous-time FPSO algorithm based on the continuous-time model of the PSO algorithm. Since the introduction of a nonlinear damping item, the continuous-time FPSO algorithm can converge over a finite-time interval. Furthermore, we will introduce a tuning parameter, which can enhance the exploration capability of the continuous-time FPSO algorithm. We will employ the Lyapunov approach to analyze continuous-time FPSO algorithm's finite-time convergence. Second, we will derive a discrete-time version of the FPSO algorithm and analyze the corresponding convergence by using an LMI approach. Finally, we will illustrate the characteristics and performance capabilities of the FPSO algorithm based on two ill-posed functions and twenty-five benchmark functions, respectively. In numerical simulation results, we will use the FPSO algorithm to deal with the problem of odor source localization.

Notation: I_N denotes the index set $\{1, 2, \ldots, N\}$. Let $\mathrm{sig}(r)^a = \mathrm{sign}(r)|r|^a$, where $0 < a < 1,\ r \in \mathbb{R}$, and $\mathrm{sign}(\cdot)$ is a sign function.

2. Background

2.1. Related works on particle swarm optimization

In the last decade, the PSO algorithm as a swarm intelligence technique has been widely studied [31]. The various versions of the PSO algorithm have been proposed to deal with different types of optimization problems, and empirical evidences indicate that the PSO algorithm is a useful tool for optimization problems [20]. The widely used version of the PSO algorithm [36] is described by

$$\begin{cases} v_i(k+1) = \omega v_i(k) + u_i(k) \\ x_i(k+1) = x_i(k) + v_i(k+1) \end{cases} \tag{1}$$

with

$$u_i(k) = \alpha_1(x_l(k) - x_i(k)) + \alpha_2(x_g(k) - x_i(k)) \tag{2}$$

where $v_i(k)$ denotes the velocity vector while $u_i(k)$ is the control vector; $x_l(k)$ refers to the previously best position of the ith particle whereas $x_g(k)$ is the globally best position of the swarm; ω is the inertia factor; and α_j $(j = 1, 2)$ are called acceleration coefficients. The PSO algorithm provides a "*decision-control mechanism*", which is analyzed in the following.

Introducing the following oscillation center $p_i(k)$ [14],

$$p_i(k) = \frac{\alpha_1 x_l(k) + \alpha_2 x_g(k)}{\alpha_1 + \alpha_2} \tag{3}$$

we have

$$u_i(k) = (\alpha_1 + \alpha_2)(p_i(k) - x_i(k)) \tag{4}$$

From (4), one can see that $u_i(k)$ can be regarded as a "P" (proportional) controller and keep the system (1) stable at the equilibrium $(0, p_i(k))$ under several conditions [15]. Therefore, each particle uses both swarm information and individual