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Generalized multi-scale dynamic inversion algorithm for electrical capacitance tomography

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ABSTRACT

Owing to distinct advantages such as the easy implementation, low cost, high safety and non-intrusive sensing, the electrical capacitance tomography (ECT) is considered as a promising visualization measurement technique, in which reconstructing high quality images is highly desirable for real applications. In this paper, a multi-scale dynamic reconstruction model, which simultaneously utilizes the ECT measurement information and the dynamic evolution information of a dynamic object, is presented. The original dynamic image reconstruction problem is decomposed into a sequence of inverse problems, which are solved successively from the largest scale to the original scale. A generalized objective functional that considers the ECT measurement information, the dynamic evolution information of a dynamic object, the temporal constraint and the spatial constraint is proposed. An iterative algorithm, which integrates the beneficial advantages of the evolutionary strategy (ES) algorithm and the homotopy method, is designed for solving the proposed objective functional. Numerical simulations are implemented to evaluate the feasibility of the proposed algorithm. For the cases simulated in this paper, the quality of the images reconstructed by the proposed algorithm is improved, which indicates that the proposed algorithm is successful in solving ECT inverse problems.

1. Introduction

Multiphase flow systems exist widely in various fields such as chemical, petrochemical, energy and power industries. Studies indicate that dynamic behaviors of the multiphase flows are extremely complicated, in which accurate measurement of the flow parameters is crucial for understanding the complicated physical mechanisms, improving system efficiency and reducing pollutant emission. Owing to advantages such as the non-intrusive sensing, high speed, low cost, easy implementation and high safety, ECT is considered as a promising visualization measurement technique. In recent years, the ECT technology has been accepted as a potential approach for exploring the complicated dynamic behaviors of the multiphase system or process, identifying the two-phase flow patterns and visualizing the distribution of the flame in the porous media [1–10].

Reconstructing high quality images plays a crucial role in real applications of ECT technology. In the past years, improving the reconstruction quality has attracted increasing attention, and various algorithms, which can be approximately divided into two categories such as the static image reconstruction algorithms and the dynamic image reconstruction algorithms, have been developed for ECT image reconstruction. Popular static image reconstruction algorithms include the linear back-projection (LBP) method [11], the Tikhonov regularization method [12], the Landweber iteration algorithm [13–15], the offline iteration and online reconstruction (OIOR) algorithm [16], the truncated singular value decomposition (TSVD) method [17], the genetic algorithm (GA) [18], the generalized vector sampled pattern matching method [19], the generalized Tikhonov regularization methods [20–23], the simulated annealing (SA) algorithm [24], the neural network algorithm [25], the level set method [26,27], the algebraic reconstruction technique (ART) and the simultaneous iterative reconstruction technique (SIRT) [17]. A detailed discussion on numerical performances of other algorithms can be found in [17,28].

In general, the above algorithms have played an important role in promoting the development of the ECT technology and found numerous successful applications. However, these algorithms fail to consider information about the temporal dynamics when the reconstruction object is in a dynamic process such as the multiphase flow and the visualization of flame. Applications indicated that ECT measurement tasks often involve time-varying objects, and it may be more reasonable to image a dynamic object using a

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dynamic reconstruction algorithm that can consider the dynamic behaviors of the objects of interest. In the field of ECT image reconstruction, dynamic reconstruction algorithms do not receive enough attention at present. Fortunately, several pioneers have investigated this subject, such as the particle filter (PF) method [29], the Kalman filter (KF) method [30] and the four-dimensional imaging method [31]. In general, the investigations of the dynamic reconstruction algorithms in the field of ECT are far from perfect, and finding an efficient dynamic reconstruction algorithm is highly desirable. Studies reveal that one of the drawbacks for ECT image reconstruction is the lack of enough quantity of information. Therefore, introducing other information in the process of ECT image reconstruction may improve the reconstruction quality. Traditional static reconstruction algorithms only consider ECT measurement information, while failing to pay attention to the dynamic information when the measurement object is in a dynamic process. At present, dynamic reconstruction algorithms, such as the PF method and the KF method, have been developed for ECT image reconstruction. However, these methods fail to simultaneously consider the temporal constraints, spatial constraints and dynamic evolution information of the objects of interest. Applications indicate that there is a close correlation among the images at different time instants when the measurement object is in a dynamic process. As a result, simultaneously considering the temporal constraints, the spatial constraints and the dynamic evolution information of the measurement objects may be essential for improving the reconstruction quality. Additionally, ECT image reconstruction process is often formulated into an optimization problem, and developing an efficient algorithm is crucial for real applications. This paper proposes a multi-scale dynamic reconstruction model, which integrates the ECT measurement information and the dynamic evolution information of a reconstruction object derived from the dynamic equations. The original image reconstruction problem is decomposed into a sequence of inverse problems, which are solved successively from the largest scale to the original scale. A generalized objective functional that simultaneously considers the ECT measurement information, the dynamic evolution information of a dynamic object, the temporal constraint and the spatial constraint is proposed. An iterative algorithm that integrates the merits of the ES algorithm and the homotopy method is designed for solving the proposed objective functional. Numerical simulations are implemented to validate the feasibility of the proposed algorithm.

The rest of this paper is organized as follows. Section 2 introduces the static model and dynamic model for ECT image reconstruction and a concise comparison on both the models is provided. In Section 3, the wavelet analysis method is introduced and a multi-scale dynamic reconstruction model is presented. A generalized objective functional is proposed in Section 4. In Section 5, the homotopy method and the ES algorithm are introduced, and an iterative scheme that integrates the advantages of the both algorithms is designed for solving the proposed objective functional. In Section 6, numerical simulations are implemented to evaluate the feasibility of the proposed algorithm, and a concise discussion on the numerical results is provided. Finally, conclusions are presented in Section 7.

2. Model representation

2.1. Static reconstruction model

ECT image reconstruction process includes two key phases: the forward problem and the inverse problem. The main motivation of the forward problem is to compute the capacitance values from the given permittivity distribution. The forward problem is a well-posed problem, and can be easily solved by numerical methods such as the finite element method and the finite difference technique. More discussions on the forward problem can be found in [11,32]. The inverse problem attempts to estimate the permittivity distribution from the known capacitance data. The inverse problem is an ill-posed problem, and special methods should be used to ensure the numerical stability of an inversion solution. Owing to the ill-posed nature of the inverse problem, the 'soft-field' effect and the under-determined problem in the process of ECT image reconstruction, exactly reconstructing the complicated objects is challenging at present.

When the inaccuracy of the measurement is considered, the static linearization ECT image reconstruction model is simplified as follows [17]:

$$\boldsymbol{S}\boldsymbol{G} = \mathbf{C} + \boldsymbol{r} \tag{1}$$

where $\boldsymbol{C}$ represents an $m \times 1$ dimensional vector indicating the normalized capacitance values; $\boldsymbol{G}$ is an $n \times 1$ dimensional vector standing for the normalized permittivity distribution, which indicates the gray level values in the reconstructed image; $\boldsymbol{S}$ stands for a matrix of dimension $m \times n$; $\boldsymbol{r}$ is an $m \times 1$ dimensional vector indicating the noises in the capacitance data.

2.2. Dynamic reconstruction model

The static reconstruction model only considers ECT measurement information; however, the dynamic evolution information of the objects of interest is not considered. Studies indicate that increasing the quantity of information in ECT image reconstruction may improve reconstruction quality. For a dynamic object, a direct approach of increasing the quantity of information is to simultaneously utilize the ECT measurement information and the dynamic evolution information of a dynamic object. As a result, a dynamic reconstruction model can be formulated by

$$\boldsymbol{G}_{k+1} = f(\boldsymbol{G}_k, \boldsymbol{v}_k) \tag{2}$$

$$\boldsymbol{y}_k = h(\boldsymbol{G}_k, \boldsymbol{n}_k) \tag{3}$$

where $\boldsymbol{G}_k$ is the unknown variable in the time instant k; f describes the dynamic evolution information, which can be expressed by a set of the partial differential equations in the multiphase flow measurement; h is called as the measurement equation; $\boldsymbol{y}_k$ represents the capacitance measurement data in the time instant k; $\boldsymbol{v}_k$ and $\boldsymbol{n}_k$ depict the uncertainties in the dynamic evolution equation and the measurement equation respectively; and the subscript k stands for the discrete time index. For achieving fast reconstruction, Eqs. (2) and (3) can be approximated by a linearization formula

$$\boldsymbol{G}_{k+1} = \boldsymbol{F}_k \boldsymbol{G}_k + \boldsymbol{v}_k \tag{4}$$

$$\overline{\boldsymbol{y}}_k = \overline{\boldsymbol{H}}_k \boldsymbol{G}_k + \overline{\boldsymbol{n}}_k \tag{5}$$

where $\boldsymbol{F}_k$ is the evolution operator in the time instant k; $\overline{\boldsymbol{H}}_k$ represents the measurement operator, which can be called as the sensitivity matrix in ECT image reconstruction. If set $\boldsymbol{F}_k = \boldsymbol{I}$, where $\boldsymbol{I}$ is the identity matrix, Eq. (4) can be considered as a purely random-walk evolution model. The model is often used in practice when a better temporal dynamic model is not known [33].

In Eq. (5), merely the measurement noises are considered. Studies indicate that the model approximation distortions derived from the linearization approximation and the approximation of a real problem may bring errors. The semiparametric model considers the above-mentioned inaccuracies, which can be formulated by [34]

$$\overline{\boldsymbol{y}}_k = \overline{\boldsymbol{H}}_k \boldsymbol{G}_k + \overline{\boldsymbol{B}}_k + \overline{\boldsymbol{n}}_k \tag{6}$$

where $\overline{\boldsymbol{B}}_k$ is an $m \times 1$ dimensional vector representing the linearization approximation errors.