

Dynamic Visualization Approach of the Multiphase Flow Using Electrical Capacitance Tomography*

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Abstract Identifying the flow patterns is vital for understanding the complicated physical mechanisms in multiphase flows. For this purpose, electrical capacitance tomography (ECT) technique is considered as a promising visualization method for the flow pattern identification, in which image reconstruction algorithms play an important role. In this paper, a generalized dynamic reconstruction model, which integrates ECT measurement information and physical evolution information of the objects of interest, was presented. A generalized objective functional that simultaneously considers the spatial constraints, temporal constraints and dynamic evolution information of the objects of interest was proposed. Numerical simulations and experiments were implemented to evaluate the feasibility and efficiency of the proposed algorithm. For the cases considered in this paper, the proposed algorithm can well reconstruct the flow patterns, and the quality of the reconstructed images is improved, which indicates that the proposed algorithm is competent to reconstruct the flow patterns in the visualization of multiphase flows.

Keywords electrical capacitance tomography, visualization, flow pattern identification, dynamic reconstruction algorithm

1 INTRODUCTION

Multiphase flow exists widely in various fields such as chemical, petrochemical and energy industries. Due to its importance, a significant number of scientific studies focusing on the characteristics of multiphase flow have been implemented. It has been proved that the behaviors of multiphase flow are extremely complicated [1, 2]. Identifying the flow patterns is vital for understanding the complicated physical mechanisms in multiphase flow. At present, different methods have been developed for identifying the flow patterns in multiphase flow, such as electrostatic method, optical method, X-ray method, γ -ray method, ultrasonic method, nuclear magnetic resonance method, electron magnetic resonance method, electrical resistance tomography, electrical impedance tomography and electrical capacitance tomography (ECT) method, and more details on different methods for the measurement of multiphase flow can be found in [3]. Overall, each method has its pros and cons, and may show different performances to different measurement objects. Owing to the characteristics and complexity of the problem, exactly identifying the flow patterns in multiphase flow is highly challenging.

Owing to the high speed, low cost, high safety and non-intrusive sensing, ECT technique is considered as a promising flow visualization approach. In recent years, ECT technology has found many successful applications in the measurement of multiphase

flow, identification of the flow patterns, and visualization of flame in porous media [4–13], showing a promising prospect.

Reconstructing high quality images plays an important role in successful applications of ECT technology. In the past years, the issue of improving the reconstruction quality has attracted increasing attention. Various algorithms have been developed for ECT image reconstruction. Overall, ECT image reconstruction algorithms can be roughly divided into two categories such as the static image reconstruction algorithms and the dynamic image reconstruction algorithms. Typical static reconstruction methods include linear back-projection (LBP) method [14], standard Tikhonov regularization (STR) method [15], Landweber iteration algorithm [16–18], offline iteration and online reconstruction (OIOR) algorithm [19], truncated singular value decomposition method [20], genetic algorithm [21], generalized vector sampled pattern matching method [22], generalized Tikhonov regularization method [23–25], simulated annealing algorithm [26], neural network algorithm [27, 28], level set method [29, 30], algebraic reconstruction technique, and simultaneous iterative reconstruction technique [20]. A review on the numerical performances and effectiveness of other algorithms can be found in [20, 31]. In general, these algorithms are successful, but they fail to consider the information about the temporal dynamics when the reconstructed object is in a dynamic process such as multiphase flow and combustion. It

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will be more reasonable to image a dynamic object using a dynamic reconstruction algorithm considering the dynamic behaviors of the objects of interest. However, the dynamic reconstruction algorithms for ECT image reconstruction do not obtain enough attention at present.

Fortunately, several early researches have explored this subject, such as the particle filter (PF) method [32], Kalman filter (KF) method [33] and four-dimensional imaging method [34]. In general, the investigations of the dynamic reconstruction algorithms in the field of ECT are far from perfect, and efficient dynamic image reconstruction algorithm is highly desirable. Studies reveal that one of drawbacks for ECT image reconstruction is to lack enough quantity of information. Therefore, introducing other information in the process of ECT image reconstruction may improve the quality of the reconstructed images. Presently, dynamic reconstruction algorithms, such as the PF method and KF method, fail to consider simultaneously the temporal constraints, spatial constraints and dynamic evolution information of the objects of interest, though applications indicate that there is a close correlation among the images in different indexes of time when the measured object is in a dynamic process.

In this paper, a generalized dynamic reconstruction model, which integrates ECT measurement information and physical evolution information of the objects of interest, was presented. A generalized objective functional that simultaneously considers the spatial constraints, the temporal constraints and the dynamic evolution information of the objects of interest was proposed. Numerical simulations and experiments were implemented to evaluate the feasibility and efficiency of the proposed algorithm, and satisfactory results were obtained.

2 DYNAMIC IMAGE RECONSTRUCTION

In this section, a dynamic reconstruction model for the identification of the flow patterns is proposed, and a generalized objective functional is described in detail. A concise comparison on the dynamic and static reconstruction models is presented.

2.1 Static image reconstruction model

Overall, a typical ECT system includes three key components: a multi-electrodes sensor, the sensing electronics for data acquisition and a computer system for image reconstruction, interpretation and display.

Based on the measured capacitance data, ECT technique attempts to reconstruct the permittivity distribution of the objects of interest via a suitable algorithm. Obviously, the efficiency of the image reconstruction algorithms plays a vital role in the successful applications of ECT.

ECT image reconstruction process involves two

key issues: the forward problem and the inverse problem. The main task of ECT forward problem is to compute the inter-electrode capacitances from the known permittivity distribution. The inverse problem aims to estimate the permittivity distribution from the known capacitance data. Owing to the ill-posed nature, the main challenge in ECT image reconstruction is the solution of the inverse problem.

In theory, the relationship between the capacitance and the permittivity distribution is expressed by the following surface integral [20]:

$$C = \frac{Q}{V} = -\frac{1}{V} \iint_{\Gamma} \varepsilon(x, y) \nabla \phi(x, y) d\Gamma \quad (1)$$

where $\varepsilon(x, y)$ is the permittivity; $\phi(x, y)$ represents the electrical potential distribution; Q is the charge; V represents the potential difference between two electrodes forming the capacitance and Γ stands for the surface of an exciting electrode.

In practice, an ECT image reconstruction model can be simplified to [20]:

$$\mathbf{SZ} = \mathbf{C} + \mathbf{r} \quad (2)$$

where $\mathbf{C}$ is a $m \times 1$ dimensional vector indicating the normalized capacitance values; $\mathbf{Z}$ is a $n \times 1$ dimensional vector standing for the normalized permittivity distribution, which stands for the gray level values in the reconstructed image; $\mathbf{S}$ represents a matrix of dimension $m \times n$, which can be called as the sensitivity in the field of ECT. More details on the solving of the sensitivity matrix can be found in [14]; $\mathbf{r}$ is a $m \times 1$ dimensional vector indicating the measurement noises.

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. ECT measurement object is often in a dynamic process such as the two-phase flow system that can be depicted by the fluid dynamics equations. Therefore, the dynamic imaging model can be formulated by

$$\mathbf{G}_{k+1} = f(\mathbf{G}_k, \mathbf{v}_k) \quad (3)$$

$$\mathbf{y}_k = h(\mathbf{G}_k, \mathbf{n}_k) \quad (4)$$

where $\mathbf{G}_k$ is the unknown variable in time k ; Eqs. (3) and (4) can be called as the process evolution equation and the measurement equation, respectively; $f(\cdot)$ describes the dynamic evolution information of the objects of interest, which can be described by a set of the partial differential equations in multiphase flow measurement; $h(\cdot)$ depicts the measurement equation; $\mathbf{y}_k$ represents the measured capacitance data in time k ; $\mathbf{v}_k$ describes the uncertainties in the process evolution equations, which is specially important for real applications because of the simplification of the theoretical model and it is hard to exactly provide the initial conditions, the boundary conditions or the physical

parameters; $\mathbf{n}_k$ depicts the uncertainties in the measurement equations owing to the fact it is hard to achieve exact measurement; subscript k represents the time index. In practice, Eqs. (3) and (4) can be approximated by a linearization formula:

$$\mathbf{G}_{k+1} = \mathbf{F}_k \mathbf{G}_k + \mathbf{v}_k \quad (5)$$

$$\mathbf{y}_k = \mathbf{H}_k \mathbf{G}_k + \mathbf{n}_k \quad (6)$$

where $\mathbf{F}_k$ is the linearization evolution operator in time k ; $\mathbf{H}_k$ represents the measurement operator, which can be called as the sensitivity matrix in ECT measurement. More details on the solving of the sensitivity matrix can be found in [14]. If set $\mathbf{F}_k = \mathbf{I}$, where $\mathbf{I}$ is the identity matrix, and Eq. (5) 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 [35]. Ideally, the nonlinear dynamic model can be incorporated into the operator $\mathbf{F}_k$.

2.3 Comparison of the static and dynamic models

Comparing the dynamic and static reconstruction models, it can be found that the static model only considers ECT measurement information; however, the dynamic model simultaneously considers the physical evolution behaviors of a dynamic object and ECT measurement information, which increases the quantity of dynamic evolution information in the process of image reconstruction.

2.4 Solving of the dynamic image reconstruction model

In this section, the design of the objective functional is based on the linearization dynamic model Eqs. (5) and (6). For the nonlinear model Eqs. (3) and (4), the derivation process is the same.

Directly solving Eqs. (5) and (6) is challenging. A popular approach is to reformulate the solution of the original problems into an optimization problem. According to the Tikhonov regularization theory and the optimization theory, the following optimization problem can be obtained:

$$\min_{\mathbf{G}_{k|k}} J = \|\mathbf{H}_k \mathbf{G}_{k|k} - \mathbf{y}_k\|^2 + \alpha \|\mathbf{G}_{k|k} - \mathbf{F}_k \mathbf{G}_{k-1|k-1}\|^2 + \alpha_1 \Omega_1(\mathbf{G}_{k|k}) \quad (7)$$

where $\alpha > 0$ and $\alpha_1 > 0$ are the regularization parameters and $\|\cdot\|$ defines the 2-norm. Particularly, item $\Omega_1(\mathbf{G}_{k|k})$ can be considered as a spatial constraint functional from the viewpoint of the Tikhonov regularization method [36].

In Eq. (7), only the spatial constraints are considered, but the temporal constraints are not considered. It is well known that measurement objects in ECT applications are often in a dynamic process, and there is a close correlation among the reconstructed

images at different frames. Therefore, considering such information may be essential for improving the reconstruction quality. Actually, in [36], the authors had proposed temporal constraint. In this paper, the temporal constraint is introduced to Eq. (7) to result in

$$\min_{\mathbf{G}_{k|k}} J = \|\mathbf{H}_k \mathbf{G}_{k|k} - \mathbf{y}_k\|^2 + \alpha \|\mathbf{G}_{k|k} - \mathbf{F}_k \mathbf{G}_{k-1|k-1}\|^2 + \alpha_1 \Omega_1(\mathbf{G}_{k|k}) + \alpha_2 \Omega_2(\mathbf{G}_{k|k} - \mathbf{G}_{k-1|k-1}) \quad (8)$$

where $\alpha_2 > 0$ is a regularization parameter; $\Omega_2(\mathbf{G}_{k|k} - \mathbf{G}_{k-1|k-1})$ represents a temporal constraint functional.

In Eq. (8), devising a suitable spatial constraint functional is vital for real applications. In this paper, the spatial constraint functional is defined as:

$$\Omega_1(\mathbf{G}_{k|k}) = \|\mathbf{W}_1 \mathbf{G}_{k|k}\|^2 \quad (9)$$

where $\mathbf{W}_1$ is a predetermined matrix.

In addition, it can be found from Eq. (8) that designing a suitable temporal constrain functional is also essential for successful applications of ECT. According to the suggestion in [36], the temporal constraint functional is defined as:

$$\Omega_2(\mathbf{G}_{k|k} - \mathbf{G}_{k-1|k-1}) = \|\mathbf{W}_2(\mathbf{G}_{k|k} - \mathbf{G}_{k-1|k-1})\|^2 \quad (10)$$

where $\mathbf{W}_2$ represents a predetermined matrix.

According to the above discussion, a generalized objective functional for ECT image reconstruction can be obtained, which can be formulated by

$$\min_{\mathbf{G}_{k|k}} J = \|\mathbf{H}_k \mathbf{G}_{k|k} - \mathbf{y}_k\|^2 + \alpha \|\mathbf{G}_{k|k} - \mathbf{F}_k \mathbf{G}_{k-1|k-1}\|^2 + \alpha_1 \|\mathbf{W}_1 \mathbf{G}_{k|k}\|^2 + \alpha_2 \|\mathbf{W}_2(\mathbf{G}_{k|k} - \mathbf{G}_{k-1|k-1})\|^2 \quad (11)$$

It is worth mentioning that Eq. (11) is built according to the linearization evolution equation and measurement equation. For the nonlinear cases, Eq. (11) can be generalized as

$$\min_{\mathbf{G}_{k|k}} J = \|\mathbf{y}_k - h(\mathbf{G}_k, \mathbf{n}_k)\|^2 + \alpha \|\mathbf{G}_{k+1} - f(\mathbf{G}_k, \mathbf{v}_k)\|^2 + \alpha_1 \|\mathbf{W}_1 \mathbf{G}_{k|k}\|^2 + \alpha_2 \|\mathbf{W}_2(\mathbf{G}_{k|k} - \mathbf{G}_{k-1|k-1})\|^2 \quad (12)$$

For easy computation, in this paper, the random-walk evolution model and the linearization measurement equation are employed. Therefore, Eq. (11) can be simplified as

$$\min_{\mathbf{G}_{k|k}} J = \|\mathbf{H}_k \mathbf{G}_{k|k} - \mathbf{y}_k\|^2 + \alpha \|\mathbf{G}_{k|k} - \mathbf{G}_{k-1|k-1}\|^2 + \alpha_1 \|\mathbf{W}_1 \mathbf{G}_{k|k}\|^2 + \alpha_2 \|\mathbf{W}_2(\mathbf{G}_{k|k} - \mathbf{G}_{k-1|k-1})\|^2 \quad (13)$$

Equation (13) is an unconstrained optimization problem. According to the optimization theory, the solution of Eq. (13) can be expressed as

$$\mathbf{G}_{k|k} = \mathbf{A}^{-1}(\mathbf{H}_k^T \mathbf{y}_k + \alpha \mathbf{G}_{k-1|k-1} + \alpha_2 \mathbf{W}_2^T \mathbf{W}_2 \mathbf{G}_{k-1|k-1}) \quad (14)$$

where $\mathbf{A} = (\mathbf{H}_k^T \mathbf{H}_k + \alpha \mathbf{I} + \alpha \mathbf{W}_1^T \mathbf{W}_1 + \alpha_2 \mathbf{W}_2^T \mathbf{W}_2)$.

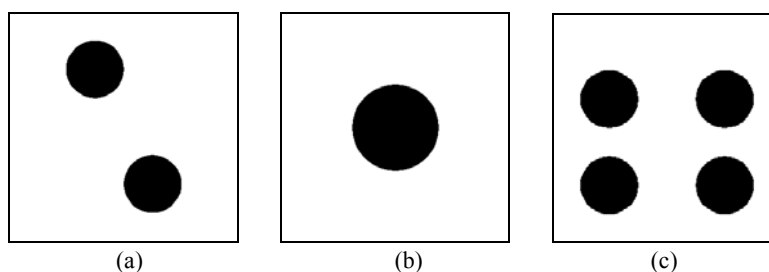


Figure 1 Original images

In practice, in order to achieve the fast measurement, $\mathbf{H}_k$ is defined as a constant matrix and matrices $\mathbf{W}_1$ and $\mathbf{W}_2$ can be predetermined. So, the expression $\mathbf{A}^{-1}$ can be computed in advance. Especially, when $\alpha = 0$, $\alpha_2 = 0$ and $\mathbf{W}_1$ is the unit matrix, Eq. (14) is equivalent to the solution of the standard Tikhonov regularization (STR) method. Obviously, the STR method is a special case of Eq. (13).

In Eqs. (13) and (14), the selection of the regularization parameter has a great influence on the final solution. At present, different methods, such as the L-curve method and the generalized cross-validation method, have been developed for selecting a suitable regularization parameter. Owing the complexity and particularity of the problem, finding an optimal regularization parameter is often determined empirically [20]. Additionally, it is worth mentioning that Eqs. (13) and (14) can be applied to both the static and dynamic reconstructions.

3 NUMERICAL SIMULATIONS

In this section, the static simulations were implemented to evaluate the feasibility and efficiency of the proposed dynamic reconstruction (DR) algorithm, and the quality of the reconstructed images were compared with the linear back-projection (LBP) method, the STR method and the projected Landweber iteration (PLI) method.

3.1 Noise-free cases

A 12 electrodes square ECT sensor is selected for simulations, and each side has three electrodes, and the size of the reconstructed region is 80 mm×80 mm. An image is presented using 32×32 pixels and each pixel takes a value between 0 and 255 on the grayscale. Three typical permittivity distributions that simulate the bubble flow in two-phase flow were chosen for image reconstruction, which are shown in Fig. 1, the black color stands for the high permittivity materials with a value of 2.6 and the white color represents the low permittivity materials with a value of 1.0. In Fig. 1 (a), the diameters of the two columns are respectively 20 mm, the permittivity of the columns is 2.6,

and the permittivity of the rest of the reconstruction region is 1.0. In Fig. 1 (b), the diameter of the column is 30 mm, the permittivity of the column is 2.6, and the permittivity of the rest of the reconstruction region is set as 1.0. In Fig. 1 (c), the diameters of the four columns are respectively 20 mm, the permittivity of the columns is 2.6, and the permittivity of the rest of the reconstruction region is defined as 1.0.

In the STR method, the values of the regularization parameters are 0.0003. The initial values for the PLI are computed by the STR method. In this section, the algorithmic parameters for the PLI method were presented in Table 1. In the DR algorithm, $\alpha = 0$, $\alpha_2 = 0$, $\alpha_1 = 0.008$, $\mathbf{W}_1 = \text{diag}\left[1/\left(\|\mathbf{G}^0\|^3 + \varepsilon\right), \dots, 1/\left(\|\mathbf{G}^0\|^3 + \varepsilon\right)\right]$, where $\varepsilon = 10^{-10}$, $\mathbf{G}^0$ is the solution of the STR method and $\text{diag}(\cdot)$ represents a diagonal matrix. Figs. 2–5 present the reconstructed images by the LBP method, STR method, PLI algorithm and the DR algorithm, respectively. The image error is used to evaluate the quality of the reconstructed images, which is listed in Table 2.

Table 1 Algorithmic parameters for the PLI algorithm

	Relaxation factor	Number of iteration
Fig. 1 (a)	1	550
Fig. 1 (b)	1	111
Fig. 1 (c)	1	405

Table 2 Image error

Algorithms	Image error/%		
	Fig. 1 (a)	Fig. 1 (b)	Fig. 1 (c)
LBP	31.32	24.84	43.21
STR	20.06	18.08	25.55
PLI	15.91	15.22	18.84
DR	9.72	11.61	14.14

Figures 2–4 show the reconstructed images by the LBP method, STR method and PLI algorithm, respectively. Numerical simulation results indicate that

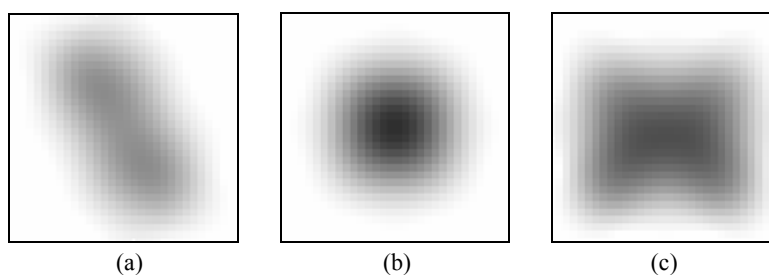


Figure 2 Reconstructed images by the LBP method

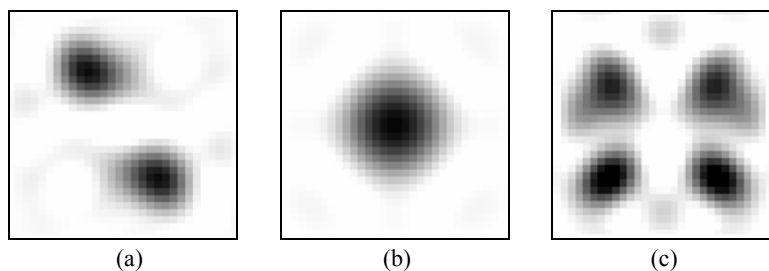


Figure 3 Reconstructed images by the STR method

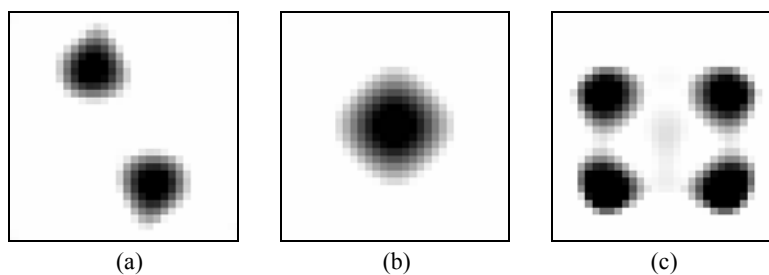


Figure 4 Reconstructed images by the PLI method

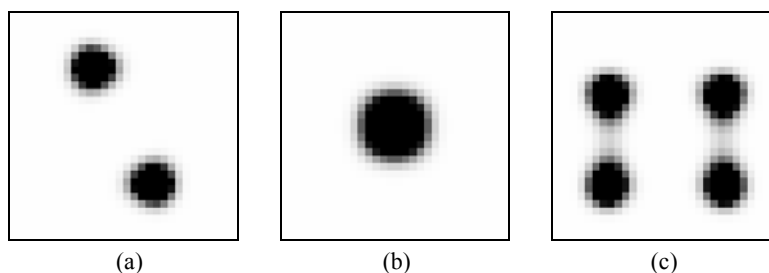


Figure 5 Reconstructed images by the DR method

the implementation of them is relatively easy. However, the quality of the reconstructed images by these three algorithms is far from satisfactory. In general, the quality of the reconstructed images by the PLI algorithm is relatively higher than the LBP method and STR method.

Numerical simulation results in Fig. 5 indicate that the DR method shows satisfactory numerical performances and can ensure the numerical stability of solution. As can be expected, for the cases simulated in this paper, the quality of the reconstructed images by the DR algorithm is improved, the spatial resolution

is increased, and the reconstruction quality is higher than the LBP method, STR method and the PLI algorithm. These reconstruction results also indicate that the DR algorithm is a promising candidate for solving ECT inverse problems. These conclusions are confirmed quantitatively by the data on image errors presented in Table 2.

3.2 Noise-contaminated cases

Applications reveal that the noises in the capacitance

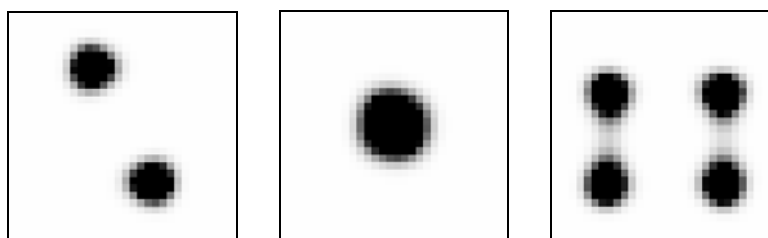


Figure 6 Reconstructed image by the DR algorithm under the noise level of 3%

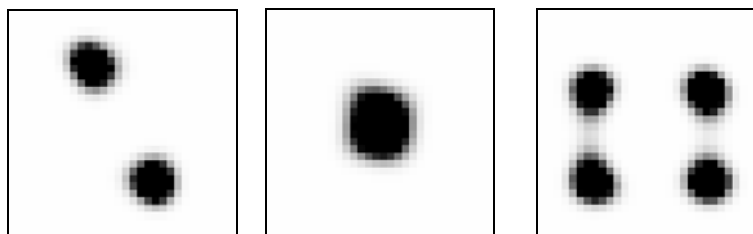


Figure 7 Reconstructed image by the DR algorithm under the noise level of 8%

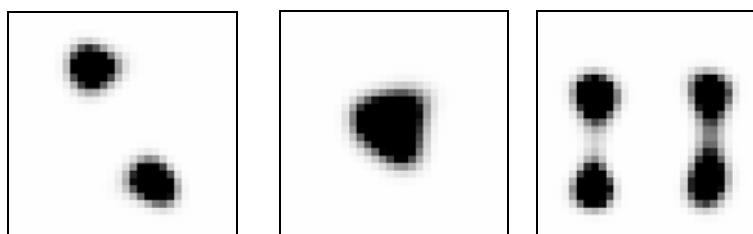


Figure 8 Reconstructed image by the DR algorithm under the noise level of 15%

data are inevitable and troublesome. A promising algorithm should have the advantage of dealing with the inaccuracy in capacitance data. In this section, the noise-contaminated capacitance data with different noise levels are used to evaluate the numerical performances and effectiveness of the DR algorithm, and the definition of the noise level can be found in [20]. Algorithmic parameters for the DR algorithm are the same as Section 3.1. Figs. 6–8 show the reconstructed images by the DR algorithm under the noise levels of 3%, 8% and 15%, respectively. The image errors under different noise levels are presented in Table 3. As can be expected, the DR algorithm shows favorable robustness to the inaccuracies in input data, and the quality of the reconstructed images is satisfactory, which is highly desirable to real application owing to the facts that achieving exact capacitance measurement is hard.

Table 3 Image error under different noise levels

Noise levels	Image error/%		
	Fig.1 (a)	Fig.1 (b)	Fig.1 (c)
3%	9.81	11.67	14.20
8%	9.99	12.97	14.77
15%	11.16	13.00	19.55

4 EXPERIMENTAL VERIFICATION

The dynamic experimental data from the gas-solid two-phase flow measurement in a CFB riser was used to evaluate the feasibility and efficiency of the DR algorithm. The permittivity of the solid particle is about 3.0, and the permittivity of the air is about 1.0.

A schematic diagram of the experimental platform is shown in Fig. 9. The experimental system consists of the air supply system, draft fan system, material circulating system and compressed air system. In particular, the ECT visualization measurement system is included in the platform. The riser section is 0.23 m in diameter and 9.8 m high, with an elbow exit. The riser entrance region has been specially designed with an air distributor to best ensure uniform air feed. Two cyclones connected in series downstream of the riser exit enables re-circulation of the solids, and solids flow rate back into the riser is controlled by a L-shape valve at the bottom of the standpipe. The geometry of standpipe is 0.30 m in diameter and 6.5 m high. The L-shape is 0.20 m in diameter and 3.24 m in length. The temperature, superficial gas velocity, and pressure data are obtained by a data acquisition system throughout the experiments. The experimental material is sand with density of $2432 \text{ kg}\cdot\text{m}^{-3}$, average diameter of

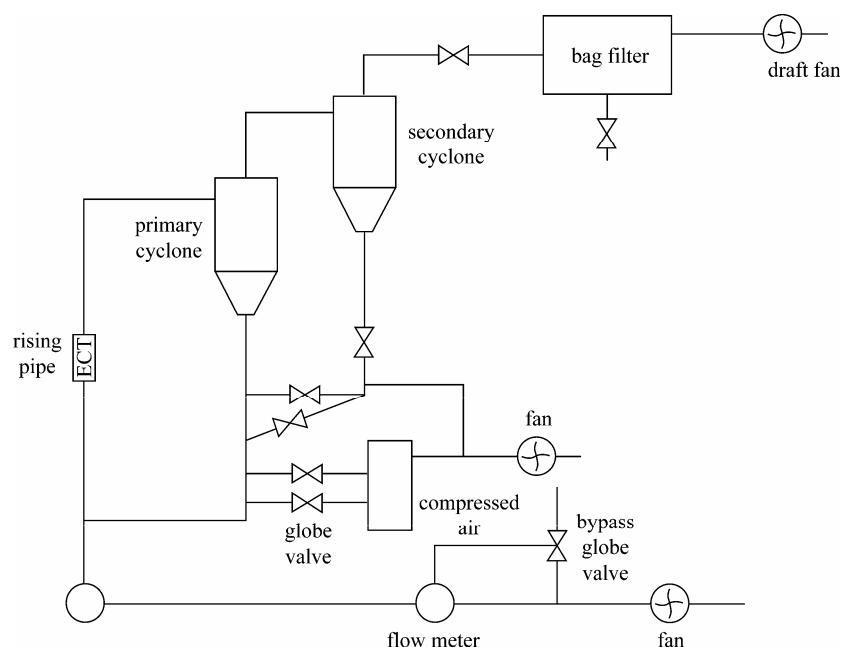


Figure 9 Experimental platform

268 μm and packed density of $1860 \text{ kg}\cdot\text{m}^{-3}$. The superficial gas velocities operated in experiments are set from $6.8 \text{ m}\cdot\text{s}^{-1}$ to $9.6 \text{ m}\cdot\text{s}^{-1}$ to obtain different gas-solid two phase flow feature in the riser. In Table 4, the superficial gas velocity is about $9.0 \text{ m}\cdot\text{s}^{-1}$, and the solids circulation rate is about $415 \text{ kg}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$.

In this experiment, a 12-electrode circle sensor, which is shown in Fig. 10, was used. The length and width of the electrode are about 100 mm and 10 mm, respectively. An image is presented using 60×60 pixels. For achieving the fast measurement, in the DR algorithm, matrices W_1 and W_2 are defined as the unit matrices. The dynamic images reconstructed by the DR algorithm are shown in Table 4.

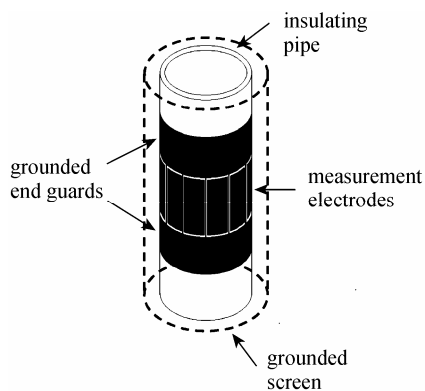


Figure 10 ECT sensor

Table 4 shows the reconstructed images by the DR algorithm for a series of time instants, and the time interval between two successive frames is about

Table 4 Reconstructed images by the DR algorithm

			
frame 7	frame 10	frame 13	frame 16
			
frame 19	frame 22	frame 25	frame 28
			
frame 31	frame 34	frame 37	frame 40

0.075 s. As can be expected, the DR algorithm shows satisfactory numerical performances, can fast reconstruct the distributions of solid particles over the cross section in a CFB riser. The typical core-annulus structure and the particle clusters can be observed. The particle concentration in the vicinity of the wall is relatively high, but in the center area the particle concentration is relative low, which is in a good agreement with those in the literature [1, 37]. In addition, it can be found from Table 4 that the shape of the core-annulus structure changes with time owing to the intense interaction between gas and solid phases. These results indicate that the DR algorithm is successful in reconstructing the dynamic objects.

5 CONCLUSIONS

In this paper, a generalized dynamic reconstruction model is proposed, which integrates ECT measurement information and physical evolution information of the objects of interest. The generalized objective functional considers simultaneously the spatial constraints, the temporal constraints and the dynamic evolution information of the objects of interest in a dynamic process. Numerical simulations and experiments were implemented to evaluate the feasibility and efficiency of the proposed algorithm. The results indicate that the proposed algorithm is feasible and can overcome the numerical instability of ECT image reconstruction owing to the fact that the Tikhonov regularization technique is introduced to the objective function. Moreover, the implementation of the proposed algorithm is easy, and the computational complexity and cost are relatively low. For the static reconstruction cases simulated in this paper, and the quality of the images reconstructed by the proposed algorithm is superior to the LBP method, STR method and the PLI algorithm. For the dynamic reconstruction cases, under the operation condition of this study, the typical core-annulus structure in the gas-solid two phase flow can be presented by ECT images, which indicate that ECT may be an alternative approach for the visualization measurement of the multiphase flow.

In this paper, a purely random-walk evolution model was employed; however, in the ongoing investigations a real physical model should be used. Overall, to enable ECT technology to be used in a real industry environment, more work on the hardware and software of ECT systems and the image reconstruction algorithms should be further implemented in the future.

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