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Evaluation on the Computational Performance of the Bubble Visualization Program

Hyu-Chan Kim* and Kyung-Ho Cho**

기포분포 가시화 프로그램의 전산특성 평가

김 휴 찬* · 조 경 호**

ABSTRACT

In this study, the EIT (Electrical Impedance Tomography) technique is applied for the two-phase flow visualization. Using the conventional EIT image reconstruction algorithms, however, the processing time increases rapidly as we try to get a higher spatial resolution. In order to overcome this problem, we added an adaptive mesh grouping method to the conventional EIT reconstruction algorithm. Performance test on the proposed mesh grouping method shows promising results that we can significantly reduce the image reconstruction time without sacrificing the spatial resolution. The mesh grouping method is found to be very effective especially in bubble distribution measurements.

Key words : Two-phase flow, Bubble visualization, Electrical impedance tomography (EIT), Mesh grouping, Fuzzy, Genetic algorithm

I. INTRODUCTION

It is very important to understand precisely the two-phase flow phenomena in the thermal hydraulic systems. Various two-phase flow measuring techniques have been suggested and devised. Based upon their principles, they can be classified into radioactive absorption and scattering[1), impedance (or capacitance)[2-5), optical[6), acoustic[7) techniques and so on. Also, these can be divided into invasive and non-invasive techniques according to whether flow fields are disturbed or not by the measuring equipments. Conductivity or optical probes are typical intrusive ones. Conversely, as non-intrusive techniques, radiological or optical equipments are adopted. Recently, many efforts are given to the development of optical techniques such as LDV (Laser Doppler Velocimetry) and PIV (Particle Image Velocimetry) methods. However, there still

* 제주한라전문대 사무자동화과
Dept. of Office Automation, Cheju Halla College
** 제주대학교 에너지공학과
Dept. of Nuclear and Energy Eng., Cheju Nat'l Univ.

remain open issues on these techniques that (i) the probes inserted into flow fields not only disturb the flow inevitably but can gather the information only at the neighboring regions around the probes and (ii) the radiological or optical methods give rather spatially-averaged information over the measured flow fields or localized information.

Recently, there are several researches[2-5] to apply the EIT (Electrical Impedance Tomography) technology[8,9] to the multi-phase as well as two-phase flow to investigate the flow mechanism more precisely. The research results, however, show that there still remain several problems to be resolved for the EIT technology to be a useful tool to measure the bubble distribution[4,5]. Even though, in two-phase flow fields, both phases may have different shapes, meshes belonging to a certain phase may have the same resistivity values. Based on this kind of observation, several researchers of biomedical engineering suggested various element or mesh grouping methods where they force all meshes belonging to certain groups to have the same resistivity values[10-12]. When meshes are appropriately grouped, we can reduce the number of variables without sacrificing the spatial resolution. This not only reduces the computation time but also improves the sensitivity problem since the size of the grouped meshes becomes bigger than the size of a single mesh. However, in all grouping methods suggested so far, meshes or elements are grouped in a pre-determined way, their usage is very limited to the specific problems. A new method is required for the bubble visualization.

In this paper, the authors' EIT static image reconstruction program[13] is further improved and tested to compare it with the existing other EIT program in regards to the reduction of the computational time and the convergence characteristics in two-phase flow visualization. The tested program has been developed using an adaptive mesh grouping method where we change the grouping of meshes during image reconstruction based on a fuzzy-genetic algorithm.

II. IMPROVED NEWTON-RAPHSON METHOD (iNR)

We adopted iNR[14] as a basic static image reconstruction algorithm. Given a computer model of a flow domain using the FEM, iNR can be formulated as follows. Fig. 1 shows FEM mesh model and a possible bubble distribution, where one mesh has one resistivity value. Assuming the resistivity distribution vector of the computer model as $\boldsymbol{\rho} = [\rho_1, \rho_2, \cdots, \rho_R]^T$ where $\rho_i \ (i = 1, \cdots, R)$ is the resistivity value of i-th element or mesh. $\boldsymbol{r} = [r_1, r_2, \cdots, r_R]^T$ is the residual error vector between the computed model boundary voltage vector $f(\boldsymbol{\rho}) = [f_1(\boldsymbol{\rho}), f_2(\boldsymbol{\rho}), \cdots, f_M(\boldsymbol{\rho})]^T$ and the measured system boundary voltage vector $\boldsymbol{v} = [v_1, v_2, \cdots, v_M]^T$. Then, the image reconstruction becomes a problem of finding $\boldsymbol{\rho}$ that minimizes the objective function defined as:

$$\min_{\boldsymbol{\rho}} \Phi(\boldsymbol{\rho})\left\{ = \sum_{i=1}^{M} r_i^2 = \sum_{i=1}^{M}\{f_i(\boldsymbol{\rho}) - v_i\}^2\right\}, \quad (1)$$

where M is the total number of boundary voltage data. The numerical solution of the minimization problem given in Eq. (1) is described in detail by Woo et al.[14].

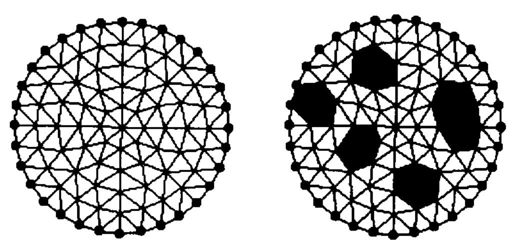


Fig. 1 FEM mesh model and 'artificial' bubbles

Since we do not know *a priori* which meshes belong to which phase, we must start with the number of unknown variables $R = \dim(\rho)$. It is, of course, much greater than the actual number of the unknown distinct resistivity values, 2 for two-phase flow fields. So it is necessary to reduce the number of the unknown variables.

Ⅲ. MESH GROUPING BASED ON FUZZY-GA

3.1. Basic idea of adaptive mesh grouping

One of the major problems in iNR is the rapid increase of the amount of computations and the poor convergence characteristics as we increase the number of unknown variables, R. However, even after a single iteration, the intermediate result provides some useful information in most cases. For example, after only a few iterations, we can obtain an approximate outline of the bubbles and tentatively decide whether a certain mesh belongs to the bubbles or to the liquid. Cheney et al.[15] proposed an algorithm called NOSER (Newton's One-Step Error Reconstructor) where they used one step of Newton's method to obtain an approximated solution of Eq. (1).

Therefore, after a few iterations of iNR, we stop and examine the intermediate results. Then, we group all meshes whose resistivity values and their changes are similar to each other. Grouping reduces R and increases the size of the effective mesh, so that it improves the condition number of the Hessian matrix in Eq. (1). By alternating iNR iterations and groupings repeatedly, we hope to improve the convergence characteristics as well as to reduce the computation time.

3.2. Three mesh groups

In two-phase flow fields, there are only two different resistivity values even though they are distributed in an arbitrary manner. One resistivity value can be considered as the resistivity of the liquid. And the other is the resistivity value of the bubble. Here, the bubble is not limited to a single segment. It could be multiple segments as long as all segments have the same resistivity value.

After a few initial iNR iterations performed without any grouping, we classify each mesh into one of three mesh groups. BaseGroup is the group of meshes with the resistivity value of the liquid. ObjectGroup is the group of meshes with the resistivity value of the bubble(s). AdjustGroup is the group of meshes neither in BaseGroup nor in ObjectGroup. All meshes in BaseGroup and ObjectGroup are forced to have the same but unknown resistivity values, respectively. However, all meshes in AdjustGroup can have different resistivity values independently.

Mesh grouping is done in two stages. In the first stage, we apply the genetic algorithm[16] to the resistivity distribution of meshes from the iNR iteration just finished. In the second stage, we examine the changes of resistivity values of each mesh during the previous several iNR iterations using the fuzzy set theory[17]. More details on the mesh grouping method can be available in another paper[13].

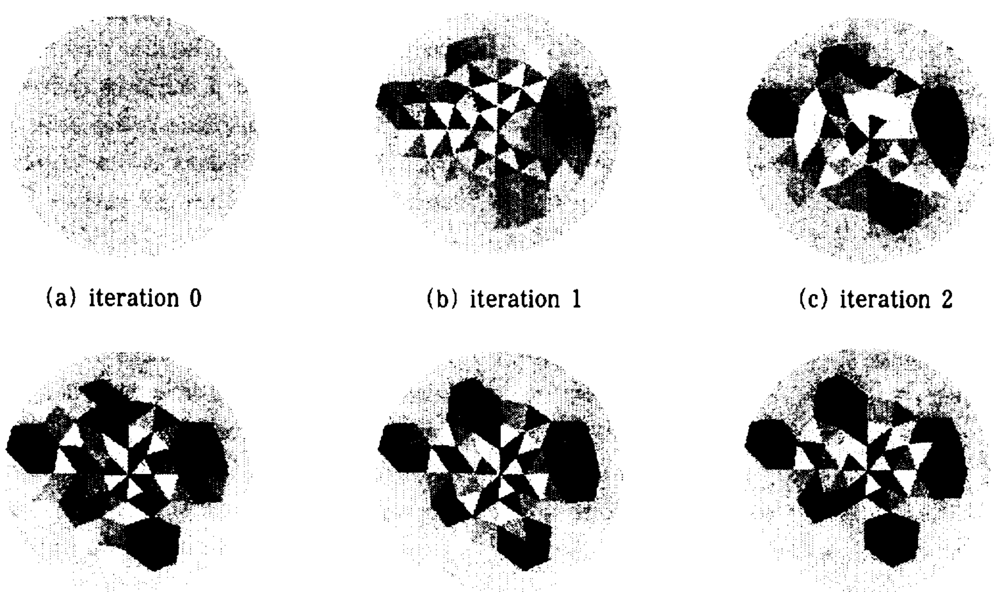
For the subsequent iNR iterations, all meshes belonging to BaseGroup and ObjectGroup are forced to have the same resistivity values as the new initial values. For meshes belonging to AdjustGroup, the average resistivity value in the group AdjustGroup is assigned as the new initial value for the next iNR iterations. However, the resistivity values in AdjustGroup can be changed independently in the subsequent iNR iterations. Therefore, the number of unknown variables is reduced to the number of meshes in AdjustGroup plus two and becomes small and small as the mesh grouping proceeds.

Ⅳ. COMPUTER SIMULATIONS

We implemented the proposed adaptive mesh grouping method based upon the iNR using C programming language. In the computer simulation, we assumed that there was no error in the data collection. We started the first iNR iteration without any mesh grouping with an arbitrary homogeneous initial guess.

Fig. 2 shows the reconstructed images for the sample 'artificial' bubbles shown in Fig. 1. Even though the pattern of the bubble distribution seems to be very simple, the iNR failed to reconstruct the bubble image correctly when the proposed mesh grouping method was not used. In Fig. 2, we may roughly estimate the profile and the location of the bubbles after only a few iterations, e.g. 5 iterations. However, further iterations result in almost little improvement. Even after 50 iterations as shown in Fig. 2(f), there still remain considerable amount of errors in the reconstructed image (see Fig. 4(a)). This kind of poor convergency is a very typical problem in the NR-type reconstruction algorithms in the EIT. However, we can significantly improve the iNR's convergency by adopting the proposed mesh grouping method as follows.

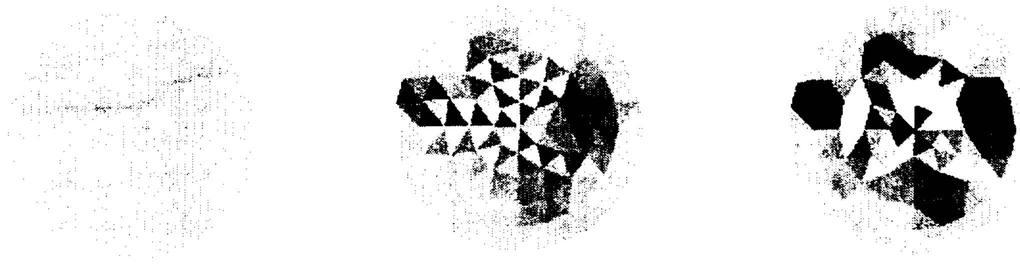
In order to apply the mesh grouping method, we stopped the initial iNR process after 5 iterations. Fig. 3(d) shows the image that is the same one in Fig. 2(d) and Fig. 3(e) shows the first mesh grouping result using the previous 5 iterations. As shown in Table 1, it should be noted that 66 meshes among 152 are grouped to BaseGroup and the remainers (darker regions in Fig. 3(e)) are grouped to AdjustGroup but none to ObjectGroup yet. The number of unknowns is reduced to 87 and the iteration time is saved by 63% approximately. Using the mesh grouping in Fig. 3(e), we restarted the second set of iNR iterations and obtained the image in Fig. 3(f) after 10 more iterations in iNR.



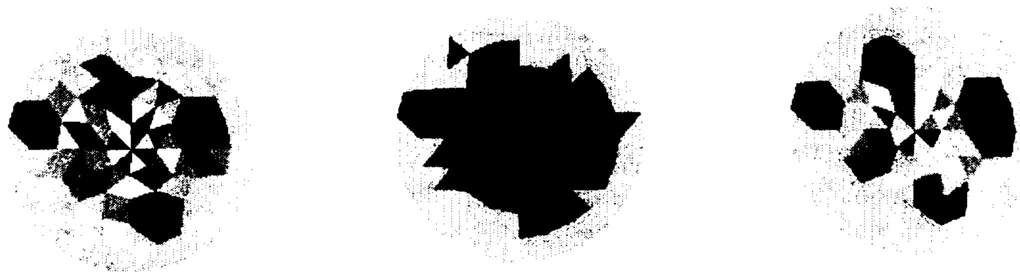
(a) iteration 0 (b) iteration 1 (c) iteration 2

(d) iteration 5 (e) iteration 20 (f) iteration 50

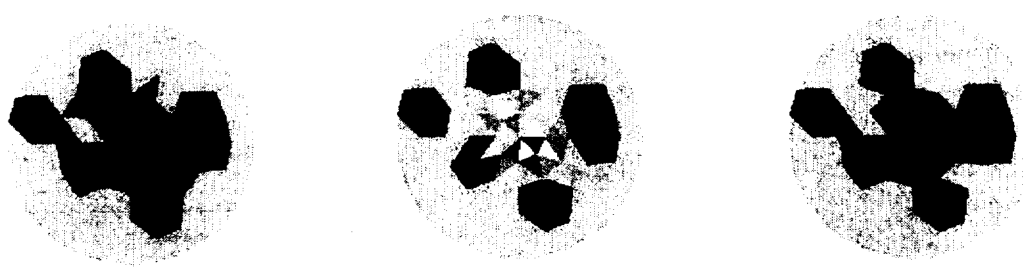
Fig. 2 Reconstructed images by iNR without mesh grouping for the 'artificial' bubbles in Fig. 1



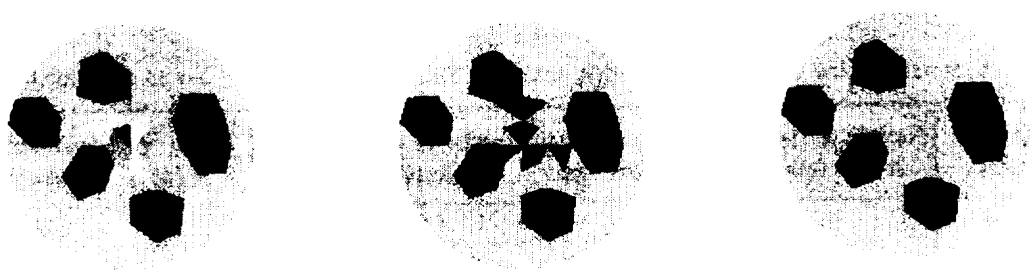
(a) iteration 0 (b) iteration 1 (c) iteration 2



(d) iteration 5 (e) 1st Grouping (f) iteration 10 after 1st Grouping



(g) 2nd Grouping (h) iteration 10 after 2nd Grouping (i) 3rd Grouping



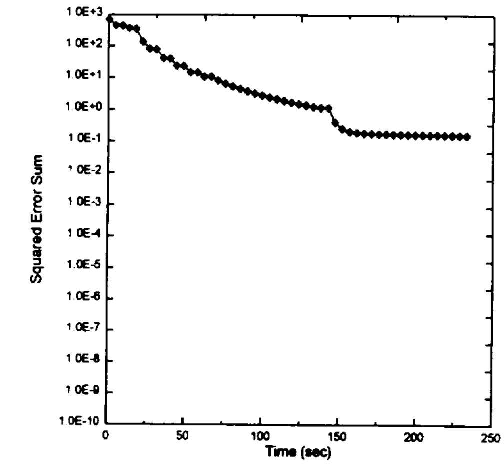
(j) iteration 10 after 3rd Grouping (k) 4th Grouping (*l*) converged image after 4th Grouping

Fig. 3 Reconstructed images by iNR with mesh gouping for the 'artificial' bubbles in Fig. 1

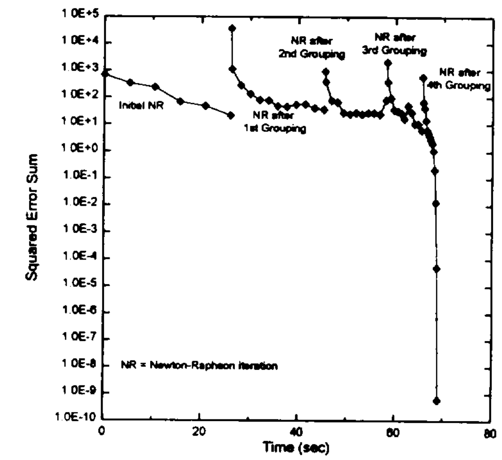
Then we stopped again and applied the second grouping to obtain the mesh grouping in Fig. 3(g). In Fig 3(i), after the third grouping, it should be noted that some meshes are now grouped to ObjectGroup and the BaseGroup becomes larger than in Fig. 3(g), so the AdjustGroup is reduced further. Repeating these procedures, we obtain the final image in Fig. 3(*l*) which is converged to the true image with the objective function value $\Phi(\rho) < 10^{-7}$ as defined by the Eq. (1).

Fig. 4 shows how the values of the objective function in Eq. (1) have changed during the image reconstruction with and without mesh grouping for the above two test cases(Figs. 2 and 3). Repeated mesh grouping helps the iNR decrease the objective value further, while the iNR without mesh grouping can't. Table 1 shows how the adaptive mesh grouping reduced the number of unknown variables and reduces computation time for a single iNR iteration when mesh grouping is adopted. By comparing two final images in Figs. 2 and 3, we can find that the proposed mesh grouping significantly improved the accuracy of the reconstructed image enhancing the convergence characteristics at reduced computation time.

Table 2 shows the summary of the four test cases for various 'artificial' bubble distributions which may be encountered in two-phase flow fields. For all the test cases, the reconstructed images are



(a) without grouping



(b) with grouping

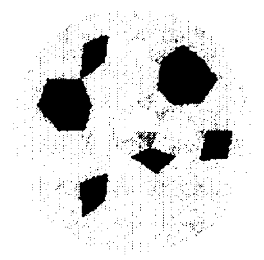
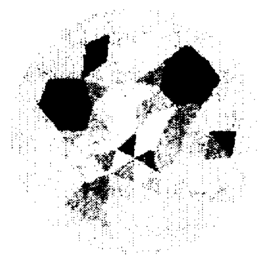
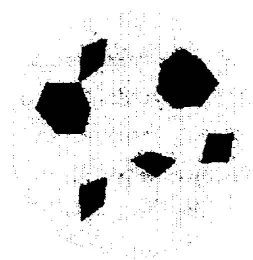
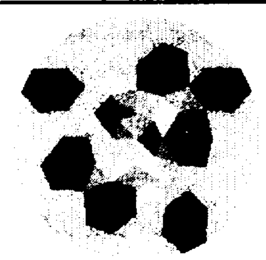
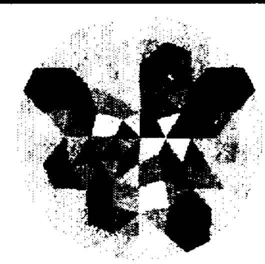
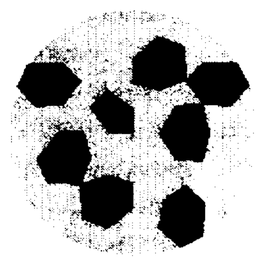
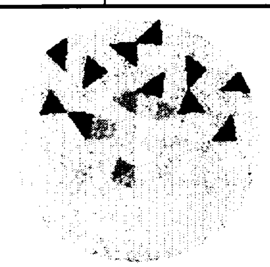
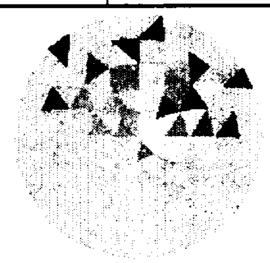
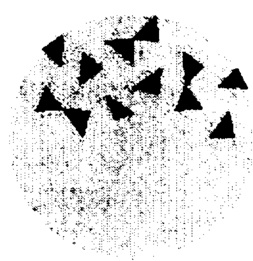
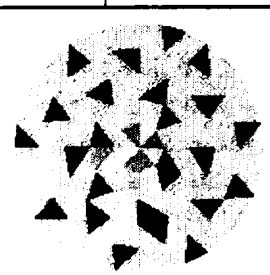
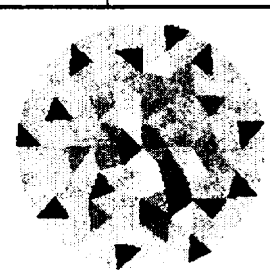
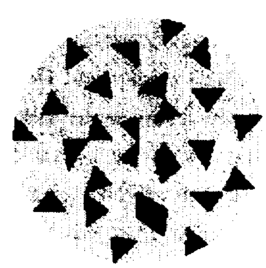
Fig. 4 Values of the objective function in Eq. (1) for images shown in Figs. 2 and 3

Table 1 Summary of the image reconstruction shown in Fig. 3 using iNR with the mesh grouping

Mesh Grouping	Number of meshes in BaseGroup	Number of meshes in ObjectGroup	Number of meshes in AdjustGroup	Number of unknown variables in iNR	Time/iteration [sec/iter]*
None	0	0	152	152	5.19
First	66	0	86	87	1.92
Second	86	0	66	67	1.29
Third	91	19	42	44	0.74
Forth	110	26	16	18	0.29

* CPU time per iteration in iNR on Pentium PC (166MHz)

Table 2 Summary of case studies for various 'artificial' bubbles

Case No.	Reconstructed Images				True Image
	with mesh grouping*		without mesh grouping		
	sec**	error $\Phi(\rho)$	sec**	error $\Phi(\rho)$	
1					
	7.41	1.53×10^{1}	165.49	9.70×10^{-1}	
2					
	28.29	5.37×10^{0}	171.97	4.38×10^{-2}	
3					
	50.20	1.15×10^{1}	162.03	2.96×10^{-1}	
4					
	65.47	9.13×10^{0}	167.91	4.05×10^{-1}	

* For all the cases above, the reconstructed images have converged to the true ones with $\Phi(\rho) < 10^{-7}$ within 5~10 seconds after the intermediate results shown above when the mesh grouping is applied.

** Elased CPU time on Pentium PC (166MHz) the intermediate ones at a certain reconstruction time described in the table. When the proposed mesh grouping method is applied, they have converged to the true images with $\Phi(\rho) < 10^{-7}$ within 5~10 seconds after the described time. On the contrary, the iNR algorithm without mesh grouping has failed to reconstruct any of these images more accurately than the images obtained with mesh grouping in spite of the longer reconstruction time. It is clear to conclude from these results that the iNR image reconstruction works better both in reconstruction time and in the quality of the reconstructed image with mesh grouping than without mesh grouping.

During many simulations, we could observe significant differences in the convergence characteristics of meshes depending on their locations. Meshes near the boundary are easily classified at the earlier reconstruction stage and converged well. On the contrary, meshes near the center take more computation time due to the poor sensitivity problem. This kind of observation coincides well with the well-known characteristics, the ill-posed phenomena in EIT.

V. CONCLUSIONS

Even though the recent researches show the potential ability of the EIT to two-phase flow fields, several problems still prevent the EIT from its practical application. One of the major problems lies in the image reconstruction time which increases very rapidly as the spatial resolution increases. The iNR method widely used at present stage also cannot be free from this kind of problem.

We developed and tested an adaptive mesh grouping method based on fuzzy-GA for the two-phase flow visualization via the EIT technique. When combined with iNR, the mesh grouping method makes significant reduction in the computation time and enhances the convergence characteristics without sacrificing spatial resolution. The accuracy of the reconstructed image was also significantly improved. So, we could always obtain almost converged images in all the conceivable cases we tried.

In this paper, we limited the implementation of the proposed mesh grouping method to a system with two unknown resistivity values. This is resonable assumption for the two-phase flow fields. We are now working on increasing the number of unknown resistivity values in order to extend the EIT to multi-phase flow fields. This will require us to divide ObjectGroup into several subgroups with different representative resistivity values.

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요 약

본 연구에서는 이상유동장 가시화를 위하여 전기임피던스 단층촬영법(EIT)을 적용하였다. 기존의 EIT 영상복원 방법에서는 분해능 향상에 따른 영상복원 시간의 급격한 증가 문제가 EIT 기법의 실용화를 어렵게 하는 가장 큰 문제점이었다. 본 연구에서는 적응적 메쉬 그룹화 방법을 토대로 개발된 EIT 영상복원 프로그램을 여러 가지의 기포분포에 적용하여 기포분포를 영상으로 복원하는 능력을 기존의 대표적인 방법과 비교하였다. 전산실험을 통한 비교결과 메쉬 그룹화 방법은 영상복원 시간의 획기적 단축뿐만 아니라, 복원된 영상의 질 면에서도 기존의 대표적인 영상복원 방법보다 우수한 결과를 보임을 확인하였다.

REFERENCES

1) Shollenberger, K.A., Torczynski, J.R., Adkins, D.R., O'Hern, T.J. and Jackson, N.B., 1997, "Gamma-Densitometry Tomography of Gas Holdup Spatial Distribution in Industrial-Scal Bubble Columns," Chem. Eng. Sci., Vol. 52, pp. 2037-2045 .
2) Dickin, F. and Yang, M., 1996, "Electrical Resistance Tomography for Process Application," Meas. Sci. Technol., Vol. 7, pp. 247-259.
3) Elkow, K.J. and Rezkallar, K.S., 1996, "Void Fraction Measurements in Gas-Liquid Flows Using Capacitance Sensor," Meas. Sci. Technol., Vol. 7, 1153
4) Ovacik, L., Lin, J.T. and Jones, O.C., 1997, "Progress in Electrical Impedance Imaging of Binary Media : 1 : Analytical and Numerical Methods," 1997 OECD/CSNI Specialists Meeting on Advanced Instrumentation, Santa Babara, CA, Mar 17 - 20
5) Ovacik, L. and Jones, O.C., 1997, "Progress in Electrical Impedance Imaging of Binary Media : 2 : Experimental Developments and Results," 1997 OECD/CSNI Specialists Meeting on Advanced Instrumentation, Santa Babara, CA, Mar 17 - 20
6) Vassallo, P.F., Trabold, T.A., Moore, W.E. and Kirouac, G.J., 1993, "Measurement of Velocities in Gas-liquid Two-phase Flow Using Laser Doppler Velocimetry," Exp. Fluids, Vol. 15, 227
7) Xu, L., Han, Y., Xu, L.A. and Yang, J., 1997, "Application of Ultrasonic Tomography to Monitoring Gas/Liquid Flow," Chem. Eng. Sci., Vol. 52, 2171
8) Webster, J.G., 1990, Electrical Impedance Tomography, Adam Hilger, Bristol, USA
9) Woo, E.J., 1990, Finite Element Method and Reconstruction Algorithms in Electrical Impedance Tomography, PhD Thesis, Dept. of Electrical and Computer Eng., Univ. Wisconsin Madison, USA
10) Woo, E.J., Hua, P., Webster, J.G. and Tompkins, W.J., 1992, "Measuring Lung Resistivity Using Electrical Impedance Tomography," IEEE Trans. Biomed. Eng., Vol. 39, 756
11) Glidewell, M. 1995, "Anatomically Constrained Electrical Impedance Tomography for Anisotropic Bodies via a Two-Step Approach," IEEE Trans. Med. Imaging, Vol. 14, 498
12) Paulsen, K.D., Meaney, P.M., Moskowitz, M.J. and Jr. Sullivan, J.M., 1995, "A Dual Mesh Scheme for Finite Element Based Reconstruction Algorithm," IEEE Trans. Med. Imaging, Vol. 14, 504
13) Cho, K.H., Woo, E.J. and Ko, S.T., 1997, "Fast Static Image Reconstruction Using Adaptive Mesh Grouping Method in EIT," Proc. 19th Int. Conf. IEEE/EMBS, Chicago, pp. 441, Oct. 30 - Nov. 2
14) Woo, E.J., Hua, P., Webster, J.G. and Tompkins, W.J., 1994, "Finite Element Method in Electrical Impedance Tomography," Med. & Biol. Eng. & Comput., Vol. 32, 530
15) Cheney, M., Isaacson, D., Newell, J. C., Simske, S. and Goble, J., 1990, "NOSER: An Algorithm for Solving the Inverse Conductivity Problem," Int. J. Imaging Syst. and Technol., Vol. 2, 66
16) Goldberg, D. E. 1989, Genetic Algorithms in Search, Optimization and Machine Learning, Addison-Wesley, New York, NY, USA
17) Zimmermann, H. J. 1996, Fuzzy Set Theory and Its Applications, Kluwer Academic, Boston, MA, USA