PARAMETRIC METHODS FOR ECT INVERSE PROBLEM SOLUTION IN SOLID FLOW MONITORING

Andrzej Romanowski, Krzysztof Grudzień, Hela Garbaa, Lidia Jackowska-Strumiłło
Lodz University of Technology, Institute of Applied Computer Science

Abstract. The article presents the parametrisation-based methods of monitoring of the process of gravitational silo discharging with aid of capacitance tomography techniques. Proposed methods cover probabilistic Bayes' modelling, including spatial and temporal analysis and Markov chain Monte Carlo methods as well as process parametrisation with artificial neural networks. In contrast to classical image reconstruction-based methods, parametric modelling allows to omit this stage as well as abandon the associated reconstruction errors. Parametric modelling enables the direct analysis of significant parameters of investigated process that in turn results in easier incorporation into the control feedback loop. Presented examples are given for the gravitational flow of bulk solids in silos.

Keywords: electrical capacitance tomography, tomography image processing, gravitational flow, granular material

METODY PARAMETRYCZNE W ROZWIĄZYWANIU PROBLEMU ODWROTNEGO DLA MONITOROWANIA PRZEPŁYWÓW MATERIAŁÓW SYPKICH

Streszczenie. Niniejszy artykuł przedstawia parametryczne metody rozwiązywania problemu odwrotnego w tomografii pojemnościowej na przykładzie monitorowania procesu przepływu materiałów sypkich przy użyciu tomografii pojemnościowej. Wybrane metody obejmują modelowanie probabilistyczne Bayesa, w tym przestrzenne i czasowe oraz metody Monte Carlo łańcuchów Markowa, a także parametryzację procesu z użyciem sztucznych sieci neuronowych. W odróżnieniu od klasycznych metod opartych na algorytmach rekonstrukcji obrazu parametryzacja pozwala na pominięcie tego etapu, a co za tym idzie brak dodatkowych błędów związanych z rekonstrukcją. Parametryzacja pozwala na bezpośrednią analizę istotnych parametrów badanego procesu, przez co łatwiejsze jest użycie tych wyników w pętli sprzężenia zwrotnego sterowania. Przykłady rozpatrywane w tekście są opisane dla procesu grawitacyjnego opróżniania materiałów sypkich przechowywanych w silosach.

Słowa kluczowe: elektryczna tomografia pojemnościowa, przetwarzanie obrazów tomograficznych, przepływ grawitacyjny, materiał sypki

Introduction

Understanding the path of retrieving the information from the tomography measurement systems is a key point of the discussion. It should be emphasized that there are different points of view on this topic. The most common is the image reconstruction based one (referred here also as the „pixel" based). It represents the group of techniques of data treatment associated with image reconstruction, processing and post-processing including numerical, statistical, etc. methodologies [1, 2, 8, 15, 18, 23, 24]. The image reconstruction itself seems to be an obvious choice when concerning process tomography, especially since 'tomography' means nothing else but drawing a picture of an inside of the investigated object [18, 22, 24, 32] (from Greek tomos and graph). However, in some cases the pixel-based philosophy is applied regardless the actual conditions; even when it is useless concerning the particular requirements of the investigation e.g. specific sort of information needed, nature of the phenomenon, etc. This supports the opposite point of view when discussing the information retrieval from the process being under investigation. According to that different philosophy the reconstruction-based data analysis methods are usually not suitable to the purpose of gaining sufficient information about the process, especially in control systems.

Pixel-based tomography has been applied in medicine, where interpretation of tomograms is traditionally accomplished with human inspection. In contrast, majority of industrial applications require quick response in terms of understanding. The process dynamics forces high data acquisition rates and, for example as for ECT and pneumatic conveying, analysis on the level of hundreds of tomograms per second is needed in order to control the process. In medical applications, the detailed imaging is almost always required, while for industrial purposes the more or less quantitative information may be sufficient in order to save process from catastrophe. The flashing red light alarming about the process failure can be enough for engineers. In such constraints of required fast response the image reconstruction solving the ill-posed inverse problem in electrical tomography needs substantial regularization. Such regularisation techniques helping to cope with inverse problem introduce unquantifiable errors [13, 21, 32], but obtained reconstruction still conveys some information. Moreover,

as we stated above, the resulting tomograms do not have to be 100% reliable as long as they satisfy their job.

In parallel to progress in image reconstruction and analysis methods an agreement on the common target: a joint model base image concept has arisen. The aim is to parameterise the image. It relies on adding knowledge about the examined phenomenon to the stage of solving inverse problem. The example of such parameterisation is presented by Isaksen and Nordtvedt [12], for oil/gas distribution in the pipeline. Parametric modelling was also applied to hydrocyclon performance investigation by West et al. [28]. The similar approach was used by McCormick and Wade [14], where tomograms were created with use of basis functions that suit the geometry of the problem. The parameters and their determination were the weights for these functions. The selection of basis functions that best represent the expected image variations is deeply investigated by Vaukhonen [27]. The key advantage of this approach, besides improving mathematical properties of the inverse problem, is the possible application in the control system, as the vector of characteristic industrial process parameters is obtained.

This paper presents overview and validation of application of the process parameterisation methodology, for ECT tomography systems and for application to granular material flow, based on two different approaches, based on Bayesian theorem and artificial neural network techniques [6, 9, 10, 19]. Different new concept of contextual input to the process of retrieval of fruitful information from the measurement system was proposed by [20]. One of the possibilities is to add some extra context awareness of the system operational conditions the other is to pre-model the system with some extra constraints such as the blockage-based fingerprinting the flow rig in order to gain contextual knowledge of the pre-malfunction and emergency states to incorporate this knowledge in normal operational conditions as proposed by authors.

1. Electrical Capacitance Tomography – classical inverse problem solution

The main idea of ECT technique is producing an image of the cross-section area within a process vessel on the basis of measurements taken on its outer boundaries in this case on the boundary of the pipe as was shown in [5, 18, 22, 24]. This is accomplished by measuring capacitance and displaying associated

permittivity distribution of a mixture of dielectric materials inside a closed pipe or a vessel. The obtained reconstructed image or image sequence can be further processed and analysed in order to acquire important information about the industrial process. The extraction of industrial process characteristic parameters based on reconstructed images is a classical approach, however sometimes it results in consumption of additional time of computation and further errors in results.

2. Inverse and forward problem in ECT system

In order to understand advantages of apply parametric modelling of process in inverse problem solutions is worth of attention to understand inverse and forward problem in process tomography systems.

In case of ECT, if the permittivity distribution ε is known, the boundary capacitance can be calculated by solving Eq.1. This is the so-called forward problem, which is non-linear, yet well-posed, and allows calculation of capacitances by the finite element method (FEM) or Boundary Elements Methods (BEM), [21].

However, the inverse problem is associated with finding the distribution of certain physical property of the material given the measurements made from the outside the body. Electrical tomography is associated with the so-called soft-field effect. In a soft-field case the electric field lines associated with the measurement are dependent on the electrical properties of the materials in the measurement space. Moreover, inverse problem in case of soft-filed tomography is ill posed and ill conditioned [13, 21, 32]. This kind of inverse problem has the property that the solution is neither unique nor stable. To deliver a practical and stable solution it is necessary to use some prior information or regularization techniques. The common practice is using the simplest non-iterative reconstruction algorithms such as LBP or Tikhonov regularization, when the time consumed on image production is the critical parameter for efficient process control and monitoring. In order to find more detailed reconstruction, when needed, the iterative methods are applied, such as Gauss-Newton; although iterative algorithms are more time consuming.

In paper we show two different approaches, which cope with these difficulties. These methods based on the Bayesian approach coupled with Markov chain Monte Carlo (MCMC) sampling and applied Neural Network ANN. Firstly, it enables delivery of a practical stable solution to the inverse problem with the aid of considerable prior information. Secondly, it allows the direct estimation of the distribution of chosen, key parameters defining the specifics of the given industrial process.

3. Gravitational flow parameterization

In paper the parameterisation of examined process will be demonstrated on example of gravitational silo discharging process. In order to determine such parametrical model it is necessary to understand the process, especially the possible material distribution and their changes inside silo over the time.

3.1. Gravitational flow of solid

Presented geometrical model for gravitational flow of bulk solids in silos monitored with ECT is based on the knowledge of the flow properties. The model divides the cross-section into the three spatial regions (Fig. 1). This model was derived based on numerous experiments and theoretical considerations for the solids flows in containers [2, 3, 4, 16, 17, 23, 25].

Movement of the bulk in the central part of the cross section is characterised by a lower packing density in contrast to the other cross-sectional region (Fig. 1a). This region is called the funnel of the flow may vary in size and shape over the time of silo unloading. The shape of the central part depends on the shape of the container outlet and the shape of the container itself (presented results are given for cylindrical silo). Another specific property of this process is the little movement of the material in the zones located close to the container's wall that actually result in a slight

increase of bulk packing density in this region. In case of funnel flow the most important is to analyse the centre of the cross section. Therefore the proposed model under consideration in this paper consists of two regions as shown on Fig 1b, [7, 10, 19]:

    a) funnel zone in the centre;

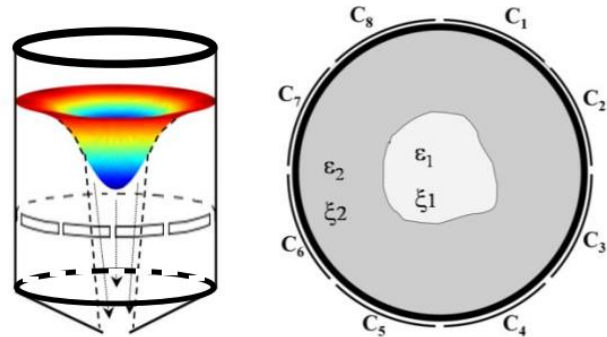   b) the rest of the container cross-section (the so-called stagnant zone)

Fig. 1. Geometrical model of silo (a) (left hand-side) simplified sketch of the container unloading with a belt of ECT electrodes depicted in a ring (b) (right hand-side) cross-sectional view of the container with a funnel indicated in the centre surrounded by the rest of the bulk. ECT electrodes belt is depicted on the outer boundary. Silo flow modelled with the set of estimated parameters η={ξ1, ε1, ξ2, ε2}

Each region is estimated with two parameters, namely: the size ξ and bulk concentration related to ε. Hence, any state of the funnel flow can be described with four 4 parameters $\gamma g=\{\xi_1, \xi_2, \varepsilon_1, \varepsilon_2\}$. Note the parameters related to the funnel are actually related to the cross-section of the funnel at a certain level of the location of the ECT electrodes belt. Geometrical modelling, i.e. parametrisation in terms of geometrical representation, allow direct estimation of process monitoring parameters, and therefore optimise use of data.

4. Bayesian approach and MCMC methods for inverse problem solution

Solving an inverse problem is looking for a relationship of the measurement (result - C) with the source data (cause - ε). This is looking for the cause, which gives the measurement. Usually there are some theoretically based expectations associated with behaviour or properties of the investigated process, and the proposed tool to incorporate this additional knowledge into solution is the Bayesian framework. Since the cause and the result can be shown as events in terms of probability – it let us use the Bayes' theorem to solve the inverse problem in tomography as was shown in [7, 10, 29, 30]. Bayes theorem in application to ECT can be presented as follows (Eq. 1):

$$p(\varepsilon|C) \propto p(C|\varepsilon) * \pi(\varepsilon) \qquad (1)$$

The formula (Eq. 1) above describes the unknown – the inverse probability, e.g. the state of the investigated object on the basis of the conducted measurement result. The term $\pi(\varepsilon)$ is called the prior probability, whereas the posterior probability term corresponds to inverse probability. As the $p(C|\varepsilon)$ term was described above to be associated with theoretical knowledge (forward probability) it can be shown as a function of cause set ε for a fixed result C. In this case we call it the likelihood function. The likelihood density function, the conditional distribution of the capacitance for a given permittivity distribution, has the following form (Eq. 2):

$$p(C|\varepsilon) = \frac{1}{(2\pi\tau^2)^{n/2}} \exp\left\{-\frac{1}{2\tau^2}\|C - C(\varepsilon)^*\|^2\right\} \qquad (2)$$

Whereas prior knowledge can be presented in form (Eq. 3):

$$\pi(\eta^t|\eta^{t-1}) \propto \exp\{-\alpha\|\eta^t - \eta^{t-1}\|_p^p\} \qquad (3)$$

where η_i^t is the set of estimated parameters at time t, parameter α stands for level of likelihood of these estimated parameters in successive time points. The prior can involve either temporal or spatial dependencies as well as convey both, spatial-temporal information. The posterior distribution can be obtained by combining the prior and likelihood.

The Markov chain Monte Carlo method is a common approach to probability density function exploration, and a Metropolis–Hastings algorithm is also an often choice. It was used to produce approximate samples from the posterior distribution by simulating a Markov chain with the posterior distribution as its equilibrium distribution as reported in [29]. Algorithm procedure is as follows: choose an arbitrary starting point – parameter value (permittivity distribution in low-level modelling or set of parameters in high – level modelling) and iterate. Changes are proposed to the parameter values at each iteration. These changes are either accepted or rejected according to a probability depending on the posterior distribution and the parameter values. Proposed values for permittivity or set of parameters were drawn from independent Gaussian distributions centred on the current parameter values. The acceptance of the proposal is dependent on the following probability formula Eq. 4:

$$\alpha(X,\Theta) = \min\left\{1, \frac{p(X|C)q((X|\Theta)}{p(\Theta|C)q(\Theta|X)}\right\} \tag{4}$$

where χ is the proposed value coming from proposal distribution $q(\chi|\Theta)$ and Θ is the set of parameter values at the previous iteration.

4.1. Incorporating prior knowledge

The exemplary process, for which the direct parameters estimation is useful, is the gravitational flow of bulk in silos as described in section 3 above. The prior knowledge involves relationship between successive parameters of measurement data (for consecutive time points), which are reasonably similar to each other, as the process is taking place relatively slowly (with respect to the measurement acquisition rate). To evaluate the likelihood, the model parameters have to be transformed into the permittivity distribution. In the above example, the permittivity distribution must be obtained from location and size parameters. In this case the area of cross–section (pixels in tomographic images) belonging to funnel was described indirectly with the aid of ellipse. Circle in the (x, y) coordinates with the centre in point (x_0, y_0) and with radius $r > 0$ is equivalent to set of all points (x, y) satisfying the Eq. 5:

$$(x - x_0)^2 + (x - y_0)^2 = r^2 \tag{5}$$

The ellipse represents the boundary between the funnel and the stagnant zone in the horizontal cross section plane of the hopper. The proposed algorithm allows transforming set of parameters into permittivity distribution in sensor space. This permittivity distribution is used in forward problem solution unit to have vector of calculated capacitance for known material distribution [7, 10].

4.2. Silo flow parameters estimation based on MCMC methods

The parameters estimation algorithm starts from the first iteration (ii=1), where the image reconstruction obtained with classical method is used as a first input for parameters calculation. Based on this reconstructed image first set of parameters is determined. The basic schema of estimation is as follows: a proposed set of parameters $\eta^{t_k} = \{\xi_1^{t_k}, \varepsilon_1^{t_k}, \xi_2^{t_k}, \varepsilon_2^{t_k}\}$ for the first frame k=1 is taken, the parameter distribution is generated, compared with capacitance measurement on the basis of solving the forward problem, accepted or rejected, then the average over all the accepted simulations is calculated. Next, this average of parameters is fitted into the proposal for the successive frames at

consecutive time points (illustrated on Fig. 2, [10]). Therefore, the temporal dependence on the previous time point is established and Markov chain is formed. The simplified graphical representation of algorithm procedure is shown on Fig. 5, [10]. The consecutive time points on the figures presented in this discussion are described with letters t with subscripts t_k, where k means the number of frame for considered measurement sequence, ii is the number of iteration in algorithm.
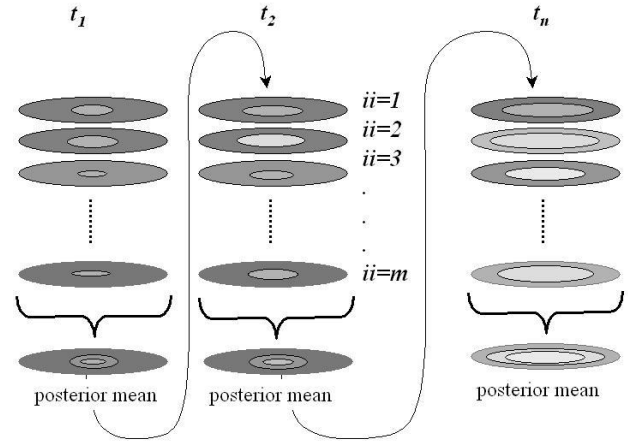

Fig.2. Algorithm diagram for silo modelling with indicated averaging after each iteration sequence for single frame estimation and fitting the posterior mean as the proposal to the next time point (ii – successive iteration index) as starting point

A plot of the estimated parameters for the silo flow shows funnel size $\xi 1$ (related to progress of hopper unloading) and the funnel permittivity $\varepsilon 1$ (related to packing density of bulk) with respect to time is shown on Fig. 3. Fig. 3a depicts the plot of the estimated area occupied by the funnel as percentage of the entire cross-section whereas Fig. 3b plots the permittivity of the funnel.
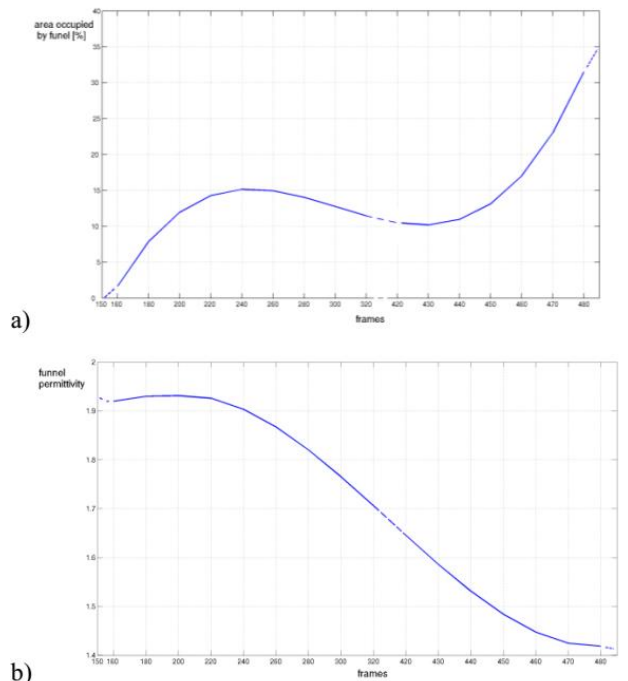

Fig. 3. Plot of estimated funnel parameters versus time, a) area occupied by funnel $\xi 1$, b) funnel permittivity $\varepsilon 1$

5. Artificial neural network methods of parameters estimation

The application of ANN to solve inverse problem for monitoring granular flow based on ECT data allows, similar as MCMC techniques, to obtain set of characteristic parameters of process. The capacitance data is fed to the artificial neural network

at the input layer and the silo flow parameters (funnel area and permittivity of the funnel) are obtained at the output layer.

ANN-based inverse model is built on the basis of relations between the network input and output vectors. The knowledge about the inverse mapping is stored within the network structure and network connection weights. An unknown mapping of the input vector to the output vector is approximated in an iterative procedure known as neural network training.

The objective of the learning algorithm is to adjust network weights on the basis of a given set of input-output pairs for a given cost function to be minimized. Back propagation algorithm, a supervised learning network algorithm, uses the gradient of the performance function to determine how to adjust the weights to minimize performance. In back propagation, the error data is propagated from the output layer backwards through the network. The resulting computations allow updating the incoming weights at each layer. Present approach propagates the network learning phase error until a set value of the training error vector is reached. The activation function $f(\cdot)$ may be a simple linear or a non-linear function. Widely used activation functions are the following: threshold function, sigmoidal function, hyperbolic tangent function and radial basis function. We employed the sigmoidal function in both hidden and output layers.

ANNs are known as universal approximators [11], which were successfully used for similar shape inverse problems solving [6, 26]. Therefore application of ANN is proposed to direct estimation of flow parameters on the basis of the measured capacitances. As shown in [26] ANN method, combined with principal component analysis, allowed real time solution of inverse problem in electrical impedance tomography.

Figure 4 shows examples of ANN applied to estimate size of funnel area. Comparison between results gathered from parametrical modelling and ANN solution (Fig. 4 left hand-side) and classical image reconstruction (Fig. 4 right hand-side) highlight the essence of deployed parametric modelling to inverse problem solving for solid flow monitoring, [6].
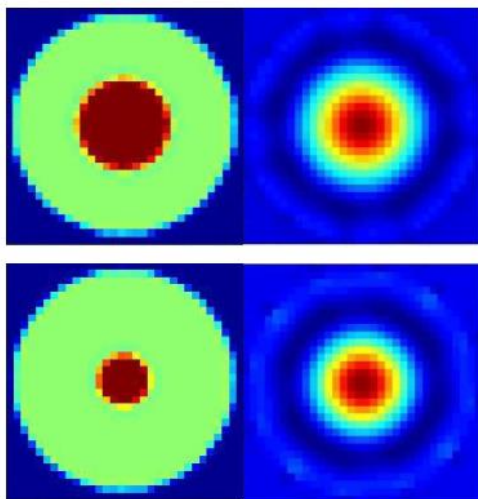

Fig. 4. Reconstructed images from MLP and Landweber algorithm

A Multi-Layer Perceptron (MLP) ANN type with one hidden layer was trained using back propagation algorithm to perform the estimation of two funnel parameters (ξ_l, ε_l) from ECT measurement data. A sequence of ECT reconstructed images for funnel flow was prepared. Comparison of the characteristic funnel parameters estimated in traditional way with the use of the Landweber method and image-processing methods with the ones estimated by the use of ANN is shown in Fig. 5.

The obtained area and permittivity of the funnel simulated by ANN are almost the same or very close to the parameters estimated in traditional way, what confirms the ability of the ANN to simulate the silo discharge process and track the changes of characteristic parameters of the flow over the time.
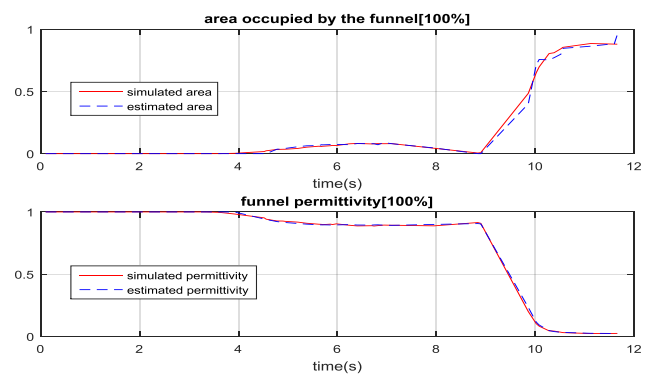

Fig. 5. ANN simulated results vs. estimated data for gravitational flow of bulk in silos. Upper diagram shows funnel area while bottom diagram presents funnel permittivity

The most important issue for ANN application is to determine the proper network structure. Such discussion was presented in [6], where different number of neurons in the hidden layer were tested. The most appropriate structure is selected relying on different chosen criteria. The trained MLP has the advantages to have simple structure one hidden layer and to directly solve the ECT inverse problem and estimate the funnel parameters (ξ_l, ε_l).

6. Discussion

Two main aspects to be considered in context of silo flow are understanding of the bulk flow behaviour and real-time monitoring of a process state. In this paper we demonstrate methods allow monitoring state of process based on tracking of characteristic parameters' changes during the flow. As demonstrated, the application of methods for silo flow behaviour monitoring with aid of process tomography and parameters estimation are feasible and fruitful. The main advantage is to omit the stage of image reconstruction on the way to analyse the measured flow behaviour. Though this advantage could be of key importance particularly in case of deployment parametrisation into the control and automation systems in the industrial settings, when the on-the-fly decision process takes place. The presented approach of direct estimation of flow parameters is beneficial especially from engineering point of view, since tracking of parameters values may allow to control process, i.e. quickly react when parameters are outside of the safe range of normal process operation. On the other hand, first step before decide what parameters should be tracked on the way to eventually incorporating this knowledge into the control feedback loop is to conduct experiments and analyse tomography images, since such analysis would allow to develop methods on how to estimate parameters based on measurement data.

ECT systems are suitable to apply in control systems, however the computational algorithms for parametrisation methods are still to be developed further. Iterative nature of MCMC methods shall be suited to on-line monitoring by both increase of computational resources (in terms of processing power and dedicated industrial FPGA hardware) and parallelisation through dedicated algorithms structures. In case on ANN methodology, time calculation is relatively short, but the actual ANN-based estimation has to be preceded with initial system learning.

The other direction for development is further regularization of the inverse problem through incorporation of more contextual data processing as proposed in [20].

7. Conclusions

Parametrisation and direct parameters estimation instead of classical image reconstruction analysis is a well advocated choice in a range of applications, especially since the inverse problem in ECT is loaded with mathematical difficulties related to nonlinearity of electric field properties. We showed here instances of two families of methods for parametrisation of gravitational

flow of bulk solids monitored with use of ECT. The first approach is Bayesian inference coupled with MCMC methods and the second possibility shown here is the employment of ANN. Both methods give sufficient accuracy allowing to produce results for both spatial and temporal modelling of process behaviour. The future work is however to develop algorithms in order to use their output parameters as input values in the industrial process control feedback loop.

References

[1] Banasiak R., Wajman R., Jaworski T., Fiderek P., Fidos H., Nowakowski J., Sankowski D.: Study on two-phase flow regime visualization and identification using 3D electrical capacitance tomography and fuzzy-logic classification. International Journal of Multiphase Flow, 58/2014, 1–14.

[2] Buick J.M., Chavez-Sagarnaga J., Zhing Z., Ooi J.Y., Pankaj D.M., Cambell D.M., Greated C.A.: Investigation of silo-honking: slip-stick excitation and wall vibration. Journal of Engineering Mechanics ASCE, 131(3)/2005, 299–307.

[3] Chaniecki Z., Dyakowski T., Niedostatkiewicz M., Sankowski D.: Application of electrical capacitance tomography for bulk solids flow analysis in silos. Particle and Particle Systems Characterization, 23(3-4)/2006, 306–312.

[4] Dhoriyani M.L., Jonnalagadda K.K., Kandikatla R.K., Rao K.K.: Silo music: sound emission during the flow of granular materials through tubes. Powder Technology, 167/2006, 55–71.

[5] Dyakowski T., Edwards R.B., Xie C.G., Williams RA.: Application of capacitance tomography to gas-solid flows. Chemical Engineering Science, 52/1997, 2099–2110.

[6] Garbaa H., Jaksowska-Strumiłło L., Grudzień K., Romanowski A.: Neural network approach to ECT Inverse problem solving for estimation of gravitational solids flow, Proceedings of the Federated Conference, Computer Science and Information Systems, 2014, 19–26.

[7] Grudzień K., Romanowski A., and Williams RA.: Application of a Bayesian Approach to the Tomographic Analysis of Hopper Flow. Particle & Particle Systems Characterization, 22/2006, 246–253.

[8] Grudzień K., Chaniecki Z., Romanowski A., Niedostatkiewicz M., Sankowski D.: Image Analysis Methods for Shear Zone Measurements during Silo Discharging Process. Chinese Journal of Chemical Engineering, 22/2012, 337–345.

[9] Grudzień K., Romanowski A., Aykroyd RG., Williams RA.: Advanced statistical computing for capacitance tomography as a monitoring and control tool. Intelligent Systems Design and Applications, 2005, 49–54.

[10] Grudzień K., Romanowski A., Aykroyd R.G., Williams R.A., Mosorov V.: Parametric Modelling Algorithms in Electrical Capacitance Tomography for Multiphase Flow Monitoring, Perspective Technologies and Methods in MEMS Design. Proceedings of the 2nd International Conference on, 2006, 100–106.

[11] Haykin S.: Neural Networks: a comprehensive foundation – 2nd ed. Prentice Hall, 1999.

[12] Isaksen Ø., Nordtvedt J.E.: A new reconstruction algorithm for use with capacitance-based tomography. Modeling, Identification and Control, 15/1994, 9–21.

[13] Lionheart W.R.B.: Review: Developments in EIT reconstruction algorithms: pitfalls, challenges and recent development. Physiol. Meas., 25/2004, 125–142.

[14] McCormick Sf., Wade J.G.: Multigrid solution of a linearized, regularized least-squares problem in electrical impedance tomography. Inverse Problems, 9/1993, 697.

[15] Mosorov V.: Flow Pattern Tracing for Mass Flow Rate Measurement in Pneumatic Conveying Using Twin Plane Electrical Capacitance Tomography. Particle & Particle Systems Characterization, 25(3)/2008, 259–265.

[16] Muite B.K., Quinn F.S., Sundaresan S., Rao K.K.: Silo music and silo quake: granular flow-induced vibration. Powder Technology, 145/2004, 190–202.

[17] Niedostatkiewicz M., Tejchman J.: Experimental and theoretical studies on resonance dynamic effects during silo flow. Powder Handling and Processing, 15(1)/2003, 36–42.

[18] Pląskowski A., Beck M.S., Thorn R., Dyakowski T.: Imaging industrial flows, applications of electrical process tomography. Institute of Physics Publishing, Bristol, 1995, 214.

[19] Romanowski A., Grudzień K., Williams R.A.: Analysis and Interpretation of Hopper Flow Behaviour Using Electrical Capacitance Tomography. Particle & Particle Systems Characterization, 23/2006, 297–305.

[20] Romanowski A., Grudzień K., Chaniecki Z., Woźniak P.: Contextual processing of ECT measurement information towards detection of process emergency states. Thirteenth International Conference on Hybdrid Intelligent Systems (HIS 2013), 2013, 292–298.

[21] Rymarczyk T., Filipowicz S.F., Sikora J.: Comparing methods of image reconstruction in electrical impedance tomography. Computer Applications In Electrical Engineering, 9/2011, 23–33.

[22] Sankowski D., Sikora J.: Electrical Capacitance Tomography: Theoretical Basis and Applications, edited by Dominik Sankowski and Jan Sikora, Wydawnictwa Książkowe Instytutu Elektrotechniki, 2010.

[23] Schulze D.: Powders and Bulk Solids, Springer, 2008, 516.

[24] Scott D.M., McCann H.: Process Imaging for automatic control, Taylor and Francis Group, 2005.

[25] Seville J.P.K., Tuzun U., Clift R.: Processing of Particulate Solids, Blackie Academic, London, 1997.

[26] Stasiak M., Sikora J., Filipowicz S.F., Nita K.: Principal component analysis and artificial neural network approach to electrical impedance tomography problems approximated by multi-region boundary element method. Engineering Analyses with Boundary Elements, 31/2007, 713–720.

[27] Vauhkonen M., Vadasz D., Karjalainen P.A., Somersalo E., Kaipio J.P.: Tikhonov regularization and prior information in electrical impedance tomography. Medical Imaging, IEEE Transactions on, 17/1998, 285–293.

[28] West R.M, Jia X, Williams R.A.: Parametric modeling in industrial process tomography. Chemical Engineering Journal, 77/2000, 31–36.

[29] West R.M., Meng S., Aykroyd R.G., Williams R.A.: Spatial-temporal modeling for electrical impedance imaging of a mixing process. Rev. Sci. Instrum. 76/2005, 073703.

[30] Winkler G.: Image Analysis, Random Fields and Markov Chain Monte Carlo: A Mathematical Introduction (2nd Ed.). Berlin, Heidelberg: Springer-Verlag., 2003.

[31] Yang W.Q., Liu S.: Role of tomography in gas/solids flow measurement. Flow Meas. and Instrum., 11/2000, 237–244.

[32] Yang W.Q., Peng L.: Image reconstruction algorithms for electrical capacitance tomography. Meas. Sci. Technol. 14/2003, R1–R13.

Ph.D. Eng. Andrzej Romanowski
e-mail: androm@kis.p.lodz.pl

Doctor of Technical Sciences, Computer Science specialized in tomography measurement data processing and inverse problems, Lodz University of Technology 2008.
Recent interests cover applications of tomography methods to industry and crowdsourcing as well as research on human factors in ubiquitous computing and human computer interaction. President of ACM and PIPS Łódź Chapters.

Ph.D. Eng. Krzysztof Grudzień
e-mail: kgrudzi@kis.p.lodz.pl

Assistant Professor of Applied Computer Science at Lodz University of Technology. Member of Polish Information Processing Society and ACM Lodz Chapter. He obtained PhD in 2007 in the field of Computer Science, Process Tomography specialty.
His research interests include applications of non-invasive imaging techniques and identification of dynamic industrial processes parameters, development of algorithms for image processing and analysis with particular reference to the analysis of sequences of 2D tomography images gathered from the ECT and X-rays tomography systems.

M.Sc. Hela Garbaa
e-mail:hgarbaa@kis.p.lodz.pl

Hela GARBAA was born in Sfax, Tunisia, in 1987. She graduated in Electrical Engineering in 2010 and obtained her Master Degree in Automatic Control and Industrial Computing from the National School of Engineers (ENIS), University of Sfax, Tunisia. She is currently a PhD student in the Institute of Applied Computer Science, Lodz University of Technology, Poland.

Prof. Lidia Jackowska-Strumiłło
e-mail: lidia_js@kis.p.lodz.pl

Professor at Lodz University of Technology (TUL), Poland and Vice-Director for didactics in the Institute of Applied Computer Science at TUL. She received the M.Sc., the Ph.D. and the DSc. degrees in electrical engineering from TUL in 1986, 1994 and 2010, respectively. In 1990/91 she has been staying in the Industrial Control Unit at the University of Strathclyde in Scotland where she worked on her Ph.D. project. From 1986 to 1998 she worked in the Institute of Textile Machines and Devices TUL.
Her research interests include computer engineering, modelling of industrial objects and processes, artificial intelligence, computer measurement systems, identification methods, text processing, image processing and analysis.