DOI: 10.5604/20830157.1201314

SIMULATION OF GRAVITATIONAL SOLIDS FLOW PROCESS AND ITS PARAMETERS ESTIMATION BY THE USE OF ELECTRICAL CAPACITANCE TOMOGRAPHY AND ARTIFICIAL NEURAL NETWORKS

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

Abstract. *The paper presents a new approach to monitoring changes of characteristic parameters of gravitational solids flow. Electrical Capacitance Tomography (ECT) is applied for non-invasive process monitoring. Artificial Neural Networks (ANN) are used to estimate important flow parameters knowing the measured capacitances. The proposed approach solves the ECT inverse problem in a direct manner and provides a rapid parameterization of the funnel flow. The simulation of the silo discharging process is performed relying on real flow behaviour obtained from the authors' previous work. The simulated data are used to new approach testing and verification. The obtained results proved that proposed ANN-based method will allow for on-line gravitational solids flow monitoring.*

Keywords: Electrical Capacitance Tomography, process simulation, Artificial Neural Networks, funnel flow parameters estimation

SYMULACJA PRZEPŁYWU GRAWITACYJNEGO I ESTYMACJA JEGO PARAMETRÓW PRZY UŻYCIU ELEKTRYCZNEJ TOMOGRAFII POJEMNOŚCIOWEJ I SZTUCZNYCH SIECI NEURONOWYCH

Streszczenie. *W artykule opisano nowe podejście do monitorowania zmian charakterystycznych parametrów przepływu grawitacyjnego. Do nieinwazyjnego monitorowania procesu stosowana jest Elektryczna Tomografia Pojemnościowa (ECT). Sztuczne Sieci Neuronowe wykorzystywane są do estymacji ważnych parametrów przepływu na podstawie mierzonych pojemności. Zaproponowane podejście pozwala na rozwiązanie problemu odwrotnego w ECT w sposób bezpośredni i umożliwia natychmiastową parametryzację przepływu kominowego. Symulacja procesu rozładowania silosu została wykonana na podstawie wyników wcześniejszych badań eksperymentalnych przeprowadzonych na rzeczywistym obiekcie. Dane symulacyjne wykorzystano do testowania i weryfikacji nowego podejścia. Uzyskane wyniki wykazały, iż zaproponowana metoda wykorzystująca Sztuczne Sieci Neuronowe pozwoli na monitorowanie on-line parametrów przepływu grawitacyjnego.*

Słowa kluczowe: elektryczna tomografia pojemnościowa, symulacja procesu, sztuczne sieci neuronowe, estymacja parametrów przepływu kominowego

Introduction

Silos are containers for protecting, storing and delivery particulate granular materials or powders. They differ on the size, shape and material of construction. A variety of types of flow regimes can be observed within the silo itself according to the geometry and solid properties. The basic two types of flow behaviour are 'mass flow' and 'core' (or 'funnel') flow. The first is characterized by all the material within any cross section discharging from the silo at the same time across the whole cross section. While the funnel flow causes problems with uniformity of flow and incomplete emptying of the hopper when the material tends to flow mainly in the core region of the container the rest of the solid situated close to walls is tending to form the so-called stagnant zones. Hence the material staying in these zones result in volume wastage and difficulties in process operation, for example uncertainty in amount and rate of material deployment into process installations [3]. Therefore funnel type of flow regime is the target of investigation in order to measure and quantify these phenomena. In the paper, authors propose estimation of two important funnel parameters: size of the funnel and permittivity of the funnel using Electrical Capacitance Tomography (ECT) and Artificial Neural Networks (ANN).

1. Electrical Capacitance Tomography and gravitational solids flow monitoring

Electrical capacitance tomography is a non-invasive measuring technique enabling visualization of the distribution of a mixture of materials with different dielectric permittivities inside an electrocapacitance sensor [5]. ECT relies on measuring the capacitances between pairs of electrodes placed around the targeted vessel (see Fig. 1). The acquired measurements are then processed to reconstruct a tomographic image by the use of an appropriate image reconstruction algorithm. Therefore ECT is a useful tool for industrial process monitoring.

The relationship between capacitance and permittivity distribution is modelled by the Gauss Law, [8] (Eq. 1):

$$C = \frac{Q}{V} = -\frac{1}{V}\iint_{\Gamma} \varepsilon(x,y)\nabla\varphi(x,y)\cdot d\boldsymbol{\Gamma}, \tag{1}$$

where: Q is the electric charge, V the potential difference between two electrodes, $\varepsilon(x, y)$ denotes the permittivity distribution and $\varphi(x, y)$ represents the electrical potential distributions. Γ stands for the electrode surface and $d\boldsymbol{\Gamma}$ an element orthogonal to this surface.

The Landweber iterative algorithm is one of the most popular methods in the field of ECT image reconstruction. The iteration process, in the Landweber algorithm is governed by the following formula [9, 13]:

$$\boldsymbol{\varepsilon}_{k+1} = \boldsymbol{\varepsilon}_k - l\,\boldsymbol{S}^T\,(\boldsymbol{S}\boldsymbol{\varepsilon}_k - \boldsymbol{C}) \tag{2}$$

where $\boldsymbol{\varepsilon}_{k+1}$ and $\boldsymbol{\varepsilon}_k$ are matrices of the estimated permittivity distributions at the k^{th} and $(k+1)^{th}$ iterations respectively, $\boldsymbol{S}$ is the calculated sensitivity matrix, l is a relaxation parameter of the Landweber algorithm and $\boldsymbol{C}$ is a matrix of measured capacitances.

The Landweber method owns the advantages of easy implementation and low computational complexity but suffers from the numerical optimization point of view as it possess a relatively low convergence rate and hardly provides a global optimization solution, [7]. Literature related to ECT application highlights that the current challenge in developing of ECT tomography concerns the improvement of the quality level of the extracted information about the state of the process in real time. In order to meet this target, new artificial intelligence techniques e.g. fuzzy logic [1] and artificial neural networks [2, 15] are applied.

In the case of controlling the funnel flow's temporal behaviour, a parameterisation of the process allows tracking the changes of characteristics parameter of the considered flow. A geometric representation of characteristic parameters of silo flow considered in this paper is shown in Fig. 1.

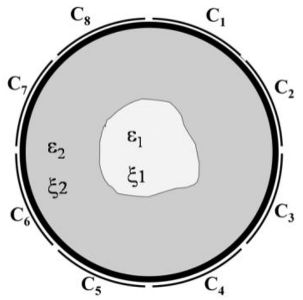

Fig. 1. Geometrical modelling of hopper flow in cross section. The set of estimated parameters $\eta = \{\xi_1, \varepsilon_1, \xi_2, \varepsilon_2\}$ [12]

This form of modelling can allow direct estimation of the process parameters, and make process monitoring more efficient.

In order to model the silo flow, two separate regions are identified within the cross section during discharging the container: the 'funnel' in the centre and the area close to wall. One region corresponds to flowing material, e.g. funnel while the other corresponds to stagnant zone. The estimated parameters were: size of the funnel ξ_1, permittivity of the funnel ε_1, and the size ξ_2 and permittivity ε_2 of the other area.

The funnel shape was approximated by a circle and its size was estimated based on the area belonging to lower permittivity ε_1 in the centre of the silo cross-section.

The changes of value of funnel permittivity can be visible on graph presenting changes of measurements capacitance in term of time during silo discharging process (Fig. 2): when the falling upper surface of the flowing solids reaches the electrode-sensing zone, measured capacitance is rising for all electrode pairs. Recorded capacitances decrease when the surface of material passes the sensors since there is less and less material present [12].

The characteristic parameters of the funnel: size and material concentration (permittivity) were estimated with the use of the Landweber method and image processing methods. Dependencies of the estimated funnel parameters versus frames are shown in Fig. 3 and 4.

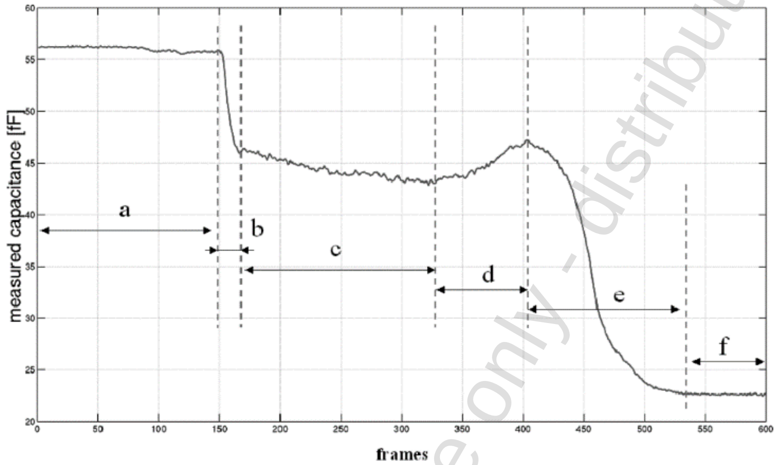

Fig. 2. Characteristics of the hopper discharge profile deduced from measured capacitance changes, showing six distinct features: (a) no change in the measurement space, (b) funnel propagation at the level of sensor plane, (c) stabilized funnel flow, (d) the flowing material surface appears at the sensor plane, (e) upper descending of the flowing material leaves the region of sensor plane, (f) residual solids in the stagnant zone

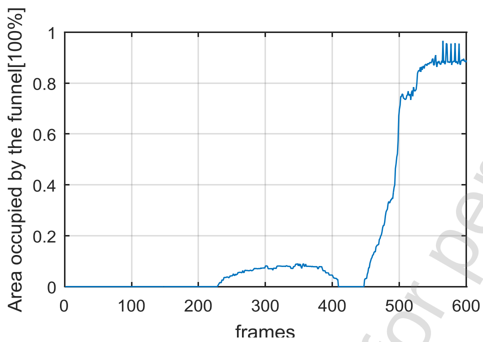

Fig. 3. Plot of the estimated area occupied by the funnel versus frames [12]

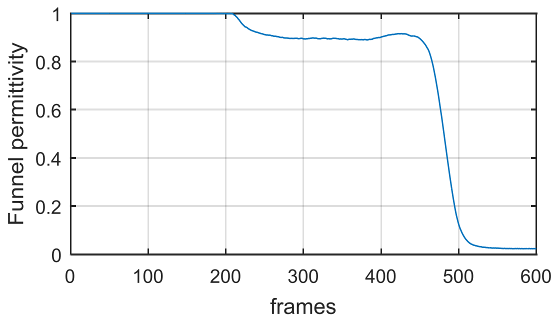

Fig. 4. Plot of the funnel permittivity ε_1 versus frames [12]

2. Flow parameters estimation by the use of Artificial Neural Networks

The main idea of the proposed approach and its comparison to the existing methods is shown in Fig. 5. The introduced approach relies on ECT to parameterize the funnel flow with no image processing step as do the existing methods. The capacitance data is fed to the artificial neural network at the input layer and the funnel area and permittivity of the funnel are obtained at the output layer.

ANNs are universal approximators [4], which were successfully used for similar shape inverse problems solving [6] and image reconstruction using electrical impedance tomography [10]. Therefore application of ANN is proposed to direct estimation of flow parameters on the basis of the measured capacitances. ANN method, combined with principal component analysis, allowed real time solution of inverse problem in electrical impedance tomography [14].

In the previous work [2], the designed ANN proved efficient results on a reduced computational time about 120 times comparing to the existing Landweber iterative algorithm for tomographic image reconstruction when estimating the radius of a circular object placed in the centre of the silo. In the present work, the performance of the ANN is tested for the occupied area by the funnel a and permittivity values ε_1 estimation.

ANN of Multi-Layer Perceptron (MLP) type with one hidden layer was trained applying back propagation algorithm to perform the estimation of two object parameters (a_1, ε_1) from ECT measurement data.

In order to test and verify the ANN performance the simulation of the silo discharging process was performed relying on real flow behaviour obtained from the authors' previous work [12].

A sequence of ECT reconstructed images obtained during funnel flow was prepared.

The set of 600 frames is divided to 540 frames for training the ANN and 60 frames to test the ability of the earlier trained to estimate the area and the permittivity of the funnel in a direct and rapid manner and thus the ability to simulate the silo discharging process.

Sum square error cost function and back propagation learning algorithm [4] were applied for the considered problem. These ensure that the convergence condition for the learning algorithm is true. In the present approach, the stop condition corresponds to a set value of the training error (TE).

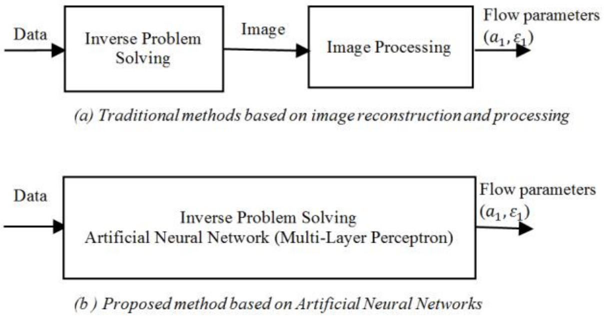

Fig. 5. Different approaches to determine the flow parameters from capacitances data: (a) an existing methods based on image processing and reconstruction, (b) the proposed method based on Artificial Neural Networks

3. Experimental results

The aim of the research was to determine the appropriate MLP structure for different radii and permittivities estimation. Different MLP structures (28-*m*-2), with 28 inputs, various numbers of neurons (*m* = 6, 8, 10 and 14) in the hidden layer and two neurons in the output layer were trained and tested (see the Table1). The neurons in the hidden layer have sigmoidal activation function, and these in the output layer have linear activation function. More than 100 different MLPs were trained.

The main criterion for choosing the best MLP structure was the minimum of mean square error (MSE) for the testing data:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left\|e_i(\boldsymbol{p})\right\|_2^2 \qquad (3)$$

where: $\|\cdot\|_2$ means Euclidean norm, $e_i(\boldsymbol{p}) = \boldsymbol{p}_i - \tilde{\boldsymbol{p}}_i$, and $\boldsymbol{p}_i$ corresponds to the desired set of parameters for *i*-th sample (a, ε), $\tilde{\boldsymbol{p}}_i$ denotes the corresponding estimated set of parameters at the MLP output and *n* is the number of testing samples.

In the selection of the appropriate MLP structure two other testing errors defined for each single shape parameter were also taken into consideration:

- Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i(p)^2} \qquad (4)$$

- Mean absolute error (ME):

$$ME = \frac{1}{n}\sum_{i=1}^{n}\left|e_i(p)\right| \qquad (5)$$

where $e_i(p) = p_i - \tilde{p}_i$, p_i corresponds to the desired single parameter ($a_i$or ε_i), for *i*-th sample, $\hat{R}\,\tilde{p}_i$ denotes the estimated parameter at MLP output and *n* the number of the testing samples.

The obtained testing errors for a training error TE = 0.01 ≈ MSE = 0.00018, are gathered in Table 1. A structure (28-10-2) provided the most satisfactory testing errors and the smallest number of iterations in the learning process. This structure was maintained to further experiments.

Table 1. Testing errors and number of iterations with different MLP structures (training error TE = 0.01 ≈ MSE= 0.000018)

Network structure	Testing error		Number of iterations (learning)
	RMSE $\left\{\begin{matrix}a\\ \varepsilon\end{matrix}\right.$	**Mean** $\left\{\begin{matrix}a\\ \varepsilon\end{matrix}\right.$	
(28-6-2)	$\left\{\begin{matrix}0.0015\\0.0010\end{matrix}\right.$	$\left\{\begin{matrix}0.0101\\0.0035\end{matrix}\right.$	45185040
(28-8-2)	$\left\{\begin{matrix}0.0017\\0.0005\end{matrix}\right.$	$\left\{\begin{matrix}0.0104\\0.0037\end{matrix}\right.$	25792020
(28-10-2)	$\left\{\begin{matrix}\mathbf{0.0002874}\\\mathbf{0.0003722}\end{matrix}\right.$	$\left\{\begin{matrix}\mathbf{0.0104}\\\mathbf{0.0038}\end{matrix}\right.$	**33487560**
(28-14-2)	$\left\{\begin{matrix}0.008\\0.0020\end{matrix}\right.$	$\left\{\begin{matrix}0.0106\\0.0046\end{matrix}\right.$	25846560

A comparison of the characteristic funnel parameters estimated in traditional way with the use of the Landweber method and image processing methods and estimated by the use of ANN is shown in Fig. 6.

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 versus time.

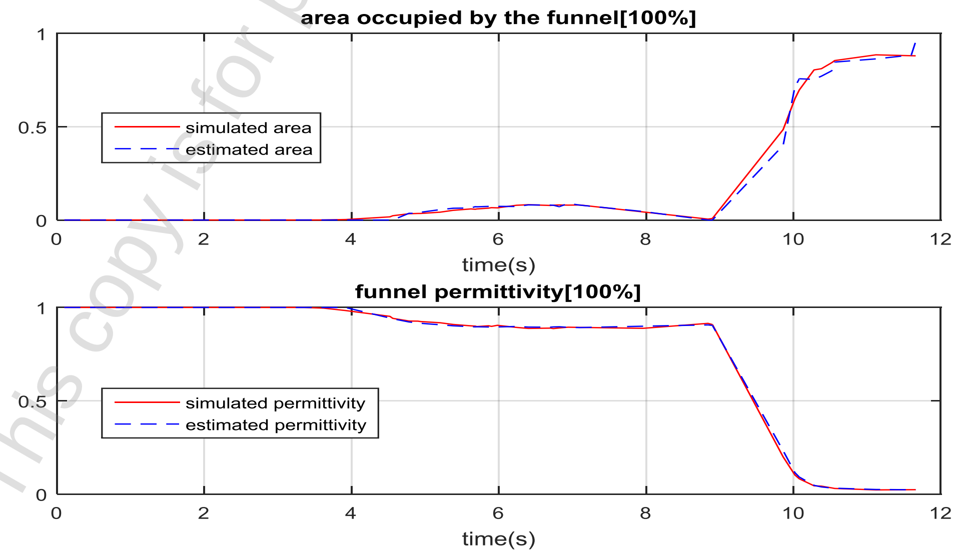

Fig. 6. Simulation in comparison to estimated data

The elapsed time of the flow parameters estimation by the trained ANN for 60 testing frames is 0.033765 second, what corresponds to 1777 frames per second. The acquisition rate, during measurements, is 50 fr/s and for high performances ECT systems the rate is 500 fr/s [11]. The proposed approach has the advantage to be rapid and the time of parameters calculation is about thirty times shorter than the acquisition time in traditional ECT measurement system and about three times shorter when compared to high performances ECT systems.

4. Conclusions

The aim of the work was to estimate the size and permittivity of the funnel during the silo discharging process based on artificial neural network technique and Electrical Capacitance Tomography. The data fed to the ANN was provided from authors previous work conducted in order to analyze and interpret the Hopper Flow behaviour using ECT.

The obtained results are promising especially under a simple MLP structure (28-10-2) and back propagation training algorithm. The provided accuracy is satisfactory and ANN based approach allowed to estimate the characteristic funnel parameters and simulate the silo discharging process in a simple manner. Results revealed potential to on-line track changes of characteristic parameters of gravitational solids flow.

Acknowledgment

Work partially funded by the European Commission under the Erasmus Mundus GreenIT project (GreenIT for the benefit of civil society. 3772227-1-2012-ES-ERAMUNDUS-EMA21; Grant Agreement nº 2012-2625/001-001-EMA2.

References

[1] Fiderek P., Wajman R., Kucharski J.: The Fuzzy System for Recognition and Control of the two Phase Gas- Liquid Flows. IAPGOS, 4/2015, 7–11.
[2] Garbaa H., Jackowska-Strumiłło L., Grudzień K., Romanowski A.: Neural network approach to ECT inverse problem solving for estimation of gravitational solids flow. Proc. of the 2014 Federated Conference on Computer Science and Information Systems (FedCSIS 2014), AAIA'14, Vol. 2, Sep. 7–10, 2014, Warsaw, Poland, 19–26 [DOI:10.15439/2014F368].
[3] Grudzień K., Romanowski A., Aykroyd R.G., Williams R.A., Mosorov V.: Parametric Modelling Algorithms in Electrical Capacitance Tomography for Multiphase Flow Monitoring, IEEE, MEMSTECH'2006, May 2006, Lviv-Polyana, Ukraine, 24–27 [DOI: 10.1109/MEMSTECH.2006.288675].
[4] Haykin S.: Neural Networks: a comprehensive foundation – 2nd ed. Prentice Hall, 1999.
[5] Isaksen Ø.: A review of reconstruction techniques for capacitance tomography. Meas. Sci. Technol. 7/1996, 325–33.
[6] Jackowska-Strumillo L., Sokolowski J., Żochowski A., Henrot A: On Numerical Solution of Shape Inverse Problems. Computational Optimization and Applications 23/2002, 231–255.
[7] Lei J., Liu S.: Dynamic Inversion Approach for Electrical Capacitance Tomography. IEEE Transactions On Instrumentation And Measurement 11/2013, 3035–3049.
[8] Lei J., Liu S., Wang X., Liu Q.: An Image Reconstruction Algorithm for Electrical Capacitance Tomography Based on Robust Principle Component Analysis. Sensors 13/2013, 2076–2092.
[9] Lionheart W.R.B.: Review: Developments in EIT reconstruction algorithms: pitfalls, challenges and recent development. Physiol. Meas. 25/2004, 125–142.
[10] Ratajewicz-Mikolajczak E., Sikora J.: Neural networks method for identification of the objects behind the screen, IEEE Trans Med Imaging 6/2002, 613–619.
[11] Rautenbach C., Mudde R.F., Yang X., Melaaen M.C., Halvorsen B.M.: A comparative study between electrical capacitance tomography and time-resolved X-ray tomography. Flow Measurement and Instrumentation 30/2013, 34–44.
[12] Romanowski A., Grudzień K., Williams R.A.: Analysis and Interpretation of Hopper Behaviour Using ECT. Part. Part. Syst. Charact. 3-4/2006, 297–305.
[13] Smolik W., Radomski D.: The matlab's toolbox for iterative image reconstruction in electrical capacitance tomography. 5th Int. Symp. on Process tomography (Poland), 98–103.
[14] 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.
[15] Warsito W., Fan L.S.: Development of 3-Dimensional Electrical Capacitance Tomography Based on Neural Network Multi-criterion Optimization Image Reconstruction. Proc. of 3rd World Congress on Industrial Process Tomography (Banff) 2003, 942–947.

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 Ph.D. student in the Institute of Applied Computer Science, Lodz University of Technology, Poland.

Prof. Eng. 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 D.Sc. 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.

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 Ph.D. 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.

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 as well as research on human factors in ubiquitous computing and human computer interaction. President of ACM and PIPS Łódź Chapters.

otrzymano/received:14.02.2016 *przyjęto do druku/accepted: 31.03.2016*