Electrical Science & Engineering
https://ojs.bilpublishing.com/index.php/ese

EDITORIAL

The Trade-off in Machine Learning Application for Electrical Impedance Tomography

Marlin Ramadhan Baidillah* **Pratondo Busono**

Research Center for Electronics, National Research and Innovation Agency (BRIN), Kawasan PUSPIPTEK, Tangerang Selatan, 15314, Indonesia

ARTICLE INFO

Article history
Received: 26 August 2022
Revised: 02 September 2022
Accepted: 05 September 2022
Published Online: 29 September 2022

In the physiological measurement science and the industrial chemical process monitoring, Electrical Impedance Tomography (EIT) as imaging technology has gained interest due to its low cost, noninvasiveness, flexibility to be customized, and non-radiation to replace the X-Ray, CT-Scan, MRI, and Ultrasonography. EIT is the evolution of Electrical Resistance Tomography (ERT) that has been widely used in the geotechnical field. In EIT, the sensor is mainly in a close boundary attached to the periphery of the human body or pipe/tank. The EIT sensor consists of a conductive circle-shaped electrode array. Through the collection of impedance measurement at very low amplitude current and less than 1 MHz frequencies, the 2D/3D electrical conductivity or permittivity distribution is reconstructed in a real-time manner to represent an object of interest such as an anomaly of physiological condition inside the human body [1], a material characterization [2], or a multiphase flow distribution inside the pipe/tank [3].

For more than three decades of EIT development study at the academic laboratories since the late 1980s, EIT's data acquisition system should be very sensitive and accurate to detect the conductivity change of the object of interest. A sophisticated impedance measurement circuit is primarily used in this requirement [4]. Meanwhile, considering the measurement time, the sophisticated impedance measurement circuit takes a lot of measurement time. Moreover, the measurement time is getting slow if a higher number of electrodes are used. In the case of multiphase flow application, the EIT system should provide a high-speed frame rate to show a reconstructed image that

*Corresponding Author:
Marlin Ramadhan Baidillah,
Research Center for Electronics, National Research and Innovation Agency (BRIN), Kawasan PUSPIPTEK, Tangerang Selatan, 15314, Indonesia;
Email: marlin.ramadhan.baidillah@brin.go.id

DOI: https://doi.org/10.30564/ese.v4i2.5000

is at least ten times higher than the speed of multiphase flow [5]. Among the three variables of EIT system performance (sensitivity, accuracy, and frame rate), prioritizing one variable will sacrifice another. Therefore, most of EIT system is customized to a particular application.

From this point, the rest of the EIT system problem is due mainly to a lack of spatial resolution. It is because the EIT uses a nonlinear current distribution, and consequently, the reconstruction of EIT is an ill-posed and ill-determined problem. The most optimum EIT system (considering the three variables as aforementioned before) still cannot guarantee a significant improvement in spatial resolution. It is still far beyond X-Ray image resolution. This issue is the main reason EIT is still difficult to go for a market. Despite reaching a higher spatial resolution to show a clear structure of the object of interest, most of the EIT system provides a robustness reconstructed image in which any small conductivity change from the object of interest can be detected and reconstructed.

To improve the robustness reconstructed image, a large amount of data from the collection of multifrequency impedance measurements in a time domain have been widely used. This is due to that the conductivity change of the object of interest is a function of frequency distribution. It is also a fundamental way to evaluate the object of interest in the frequency spectrum of reconstructed images [6,7]. Additionally, the conductivity of change of the object of interest occurs in the time domain monitoring or imaging [8]. Moreover, integrating with other modalities with different sensor configurations could be possible such as with electrical capacitance tomography (ECT) [9,10], mutual inductance tomography (MIT) [11], and Ultrasonography [12]. The dual modalities system causes a more complicated sensor and takes a longer measurement time; however, it may provide a prominent result in the most sophisticated system.

Following the effort to improve the robustness of reconstructed images, machine learning (ML) is currently employed [13]. Remember that a high computational cost and a complex regularization to solve the reconstruction problem are troublesome and time-consuming in the case of the ill-posed and ill-determined case. In order to bypass the problem of conventional reconstruction processing, the ML predicts the true conductivity distribution by governing a neural network trained in the initial condition of EIT measurement. Some promising studies show the performance of ML, such as prediction of the most optimum scanning measurement pattern [14], restoration of reconstructed image [15], estimation of the object of interest without an image [16], and recognition of hand prosthesis control [17].

In ML applications for EIT, a predictive model is developed through neural network training from a data set collection. For image classification, a convolutional neural network (CNN) is commonly used because its assigning of important variables (such as learnable weights and biases) to various features in the image will be able to differentiate each other [18]. Meanwhile, a Long Short-Term Memory (LSTM) network for the case of time-domain data because of its feedback connection among the data points in the entire sequence [19]. The predictive model is very sensitive to the random selection of initial parameters. This random selection causes the predictive model becomes more difficult to be duplicated even using the same training dataset and ML framework algorithm (including model parameter, and optimization functions). Thus, governing the predicted model should be evaluated with some different frameworks.

The most critical accuracy issue of the predictive model from a neural network training is based on the proper classification data on the data set, which has the desired feature extracted from the object of interest in the prior condition of EIT measurement. Different application has their own different feature. In EIT for physiological measurement, a conductivity change related to a particular physiological condition or disease is biased by other confounding factor such as systematical error during the measurement, unknown contact impedance, temperature change, and boundary change. Thus, it is crucial to discriminate the confounding factors of EIT during the measurement. Otherwise, the output of ML will be misinterpreted.

Finally, the maturity of ML application for EIT will be limited to an early warning system instead of a true physiological condition. Though, we can still obtain this benefit by observing the predictive conductivity distribution without suffering the ill-posed problem in the reconstruction image. Moreover, in a straightforward method, a predictive model without using a reconstructed image but providing the binary data results representing the true feature of the object of interest could be challenging and interesting for future EIT applications [20].

Conflict of Interest

There is no conflict of interest.

References

[1] Brown, B.H., 2003. Electrical impedance tomography

(EIT): A review. Journal of Medical Engineering & Technology. 27(3), 97-108.
DOI: https://doi.org/10.1080/0309190021000059687

[2] Khambampati, A.K., Rahman, S.A., Sharma, S.K., et al., 2022. Nonlinear difference imaging to image local conductivity of single-layer graphene using electrical impedance tomography. IEEE Transactions on Instrumentation and Measurement.
DOI: https://doi.org/10.1109/TIM.2022.3147894

[3] Yao, J., Takei, M., 2017. Application of Process Tomography to Multiphase Flow Measurement in Industrial and Biomedical Fields - A Review. IEEE Sensors Journal. pp. 1.
DOI: https://doi.org/10.1109/JSEN.2017.2682929

[4] Hahn, G., Just, A., Dittmar, J., et al., 2008. Systematic errors of EIT systems determined by easily-scalable resistive phantoms. Physiological Measurement. 29(6), S163-172.
DOI: https://doi.org/10.1088/0967-3334/29/6/S14

[5] Cook, R.D., Saulnier, G.J., Gisser, D.G., et al., 1994. ACT3: a high-speed, high-precision electrical impedance tomograph. IEEE Transactions on Biomedical Engineering. 41(8), 713-722.
DOI: https://doi.org/10.1109/10.310086

[6] Baidillah, M.R., Iman, A.A.S., Sun, Y., et al., 2017. Electrical Impedance Spectro-Tomography based on Dielectric Relaxation Model. IEEE Sensors Journal. 17(24), 8251-8262.
DOI: https://doi.org/10.1109/JSEN.2017.2710146

[7] Hoyle, B.S., Nahvi, M., 2008. Spectro-tomography - an electrical sensing method for integrated estimation of component identification and distribution mapping in industrial processes. 2008 IEEE Sensors. pp. 807-810.
DOI: https://doi.org/10.1109/ICSENS.2008.4716564

[8] Ogawa, R., Baidillah, M.R., Akita, S., et al., 2020. Investigation of physiological swelling on conductivity distribution in lower leg subcutaneous tissue by electrical impedance tomography. Journal of Electrical Bioimpedance. 11(1), 19-25.
DOI: https://doi.org/10.2478/joeb-2020-0004

[9] Marashdeh, Q., Warsito, W., Fan, L.S., et al., 2006. An Impedance Tomography system based on ECT sensor. IEEE Sensors Journal. 1(11), 1-7.

[10] Wang, Q., Wang, M., Wei, K., et al., 2017. Visualization of Gas-Oil-Water Flow in Horizontal Pipeline Using Dual-Modality Electrical Tomographic Systems. IEEE Sensors Journal. 17(24), 8146-8156.
DOI: https://doi.org/10.1109/JSEN.2017.2714686

[11] Gürsoy, D., Mamatjan, Y., Adler, A., et al., 2011. Enhancing impedance imaging through multimodal tomography. IEEE Transactions on Biomedical Engineering. 58(11), 3215-3224.
DOI: https://doi.org/10.1109/TBME.2011.2165714

[12] Choridah, L., Kurniadi, D., Ain, K., et al., 2021. Comparison of Electrical Impedance Tomography and Ultrasonography for Determination of Solid and Cystic Lesion Resembling Breast Tumor Embedded in Chicken Phantom. Journal of Electrical Bioimpedance. 12(1), 63.
DOI: https://doi.org/10.2478/joeb-2021-0008

[13] Dy, J.G., Brodley, C.E., Kak, A., et al., 2003. Unsupervised feature selection applied to content-based retrieval of lung images. IEEE Transactions on Pattern Analysis and Machine Intelligence. 25(3), 373-378.
DOI: https://doi.org/10.1109/TPAMI.2003.1182100

[14] Rymarczyk, T., Kłosowski, G., Hoła, A., et al., 2022. Optimising the use of Machine learning algorithms in electrical tomography of building Walls: Pixel oriented ensemble approach. Measurement. 188, 110581.
DOI: https://doi.org/10.1016/j.measurement.2021.110581

[15] Coxson, A., Mihov, I., Wang, Z., et al., 2022. Machine learning enhanced electrical impedance tomography for 2D materials. Inverse Problems. 38(8), 085007.

[16] Tanaka, K., Prayitno, Y.A.K., Sejati, P.A., et al., 2022. Void fraction estimation in vertical gas-liquid flow by plural long short-term memory with sparse model implemented in multiple current-voltage system. Multiphase Science and Technology. 34(2).

[17] Wu, Y., Jiang, D., Liu, X., et al., 2018. A Human-Machine Interface Using Electrical Impedance Tomography for Hand Prosthesis Control. IEEE Transactions on Biomedical Circuits and Systems. 12(6), 1322-1333.
DOI: https://doi.org/10.1109/TBCAS.2018.2878395

[18] Valueva, M.V., Nagornov, N.N., Lyakhov, P.A., et al., 2020. Application of the residue number system to reduce hardware costs of the convolutional neural network implementation. Mathematics and Computers in Simulation. 177, 232-243.
DOI: https://doi.org/10.1016/j.matcom.2020.04.031

[19] Hochreiter, S., Schmidhuber, J., 1997. Long Short-Term Memory. Neural Computation. 9(8), 1735-1780.

[20] Lee, H., Huang, C., Yune, S., et al., 2019. Machine Friendly Machine Learning: Interpretation of Computed Tomography Without Image Reconstruction. Scientific Reports. 9(1), 1-9.
DOI: https://doi.org/10.1038/s41598-019-51779-5