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Machine learning in image reconstruction by multi-sensor electrodes

***Abstract**. The article presents a system that uses machine learning to reconstruct the image using multi-sensor electrodes based on electric tomography. It is an innovative approach to testing the properties of test areas, including levees. The measuring system was based on an electric tomography device, which assumes the use of two measuring methods and allows measurements to be made to 32 channels. The device based on electric impedance tomography measures the tested object based on the potential distribution measurements. The system collects measured data from the electrodes. In the process of image reconstruction, the elastic net method was used, where appropriate regularization methods help in choosing the optimal solution..*

***Streszczenie.** W artykule przedstawiono system wykorzystujący uczenie maszynowe do rekonstrukcji obrazu za pomocą elektrod wieloczujnikowych oparty na tomografii elektrycznej. Jest to innowacyjne podejście do badania właściwości obszarów testowych, w tym wałów przeciwpowodziowych. System pomiarowy został oparty na urządzeniu do tomografii elektrycznej, który zakłada stosowanie dwóch metod pomiarowych i umożliwia wykonanie pomiarów do 32 kanałów. Urządzenie oparte na elektrycznej tomografii impedancyjnej mierzy badany obiekt w oparciu o pomiary rozkładu potencjału. System zbiera zmierzone dane z elektrod. W procesie rekonstrukcji obrazu zastosowana metodę elastycznej siatki, gdzie odpowiednie metody regularyzacji pomagają w wyborze optymalnego rozwiązania.. (**Uczenie maszynowe w rekonstrukcji obrazu z użyciem elektrod wieloczujnikowych**).*

Keywords: electrical impedance tomography, machine learning, inverse problem.
Słowa kluczowe: elektryczna tomografia impedancyjna, uczenie maszynowe, zagadnienie odwrotne.

Introduction

In electrical impedance tomography (EIT), voltage or current is injected into an object using a set of electrodes attached to its surface [1-6]. Voltage values are measured on the remaining electrodes. The conductivity of the object is reconstructed based on the measurements taken and the appropriate algorithm to solve the inverse problem [7-19].

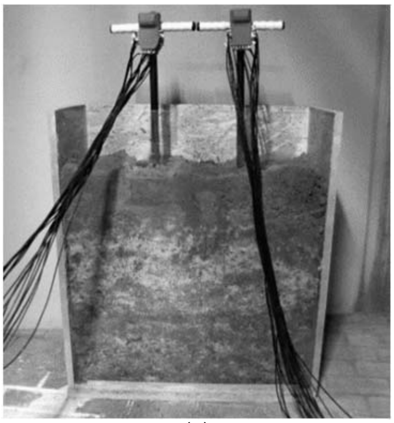
Measurement system

The measuring system was based on an electric tomography device, which assumes the use of two measuring methods and allows measurements to be made to 32 channels. Figure 1 shows laboratory measurement models with one and two multi-sensor electrodes. The device measures the tested object based on measurements of the potential distribution on the surface. The system collects measured data from the electrodes. The solution assumes the use of two measuring methods and allows measurements to be made to 32 channels.

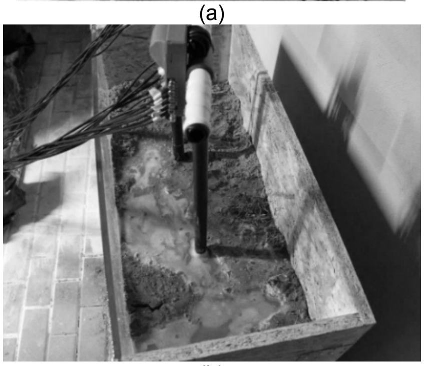
The device consists of several separate modules: power generator, measuring block, multiplexer and controller. You can connect more than one multiplexer to the device. Data acquisition systems require equipment for voltage measurement, filtering, demodulation and conversion to digital units and signal processing in order to send data to the computing unit. Depending on the method of use, the system can be adapted to measurements in large areas or small sections. In both cases, all infrastructure is centrally managed to collect data and record measurements. The system allows you to collect measurements, manage data and monitor devices. An electric tomograph constructed for this type of measurement is shown in Fig. 2.

Methods

There are many numerical methods used in optimization problems [20-35]. This article uses machine learning methods [36-39] that use information to learn directly from data without first determining a mathematical model. The machine learning algorithms used utilize the availability of large amounts of data and computing resources. The main idea is to prepare a model from a finished training set that generalizes the characteristic properties of the problem being studied. This model reflects the real problem based on prepared and trained examples.



(a)



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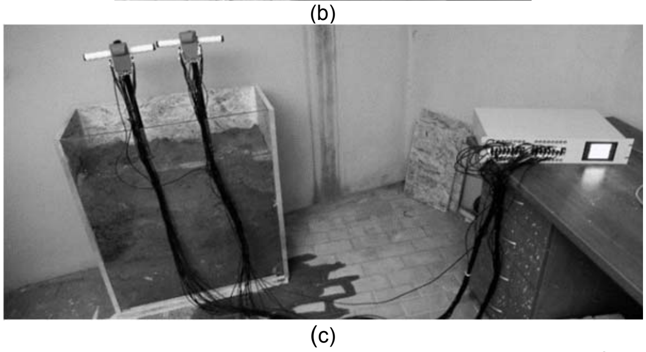


(c)

Fig.1. Laboratory model with one multi-sensor electrode: a) front view, b) top view, c) measurement system.

Fig.2. An electrical tomograph for measurements in electrical tomography.

The data analyzed is often highly correlated and it is necessary to select important groups of variables. The least squares method is used to estimate the parameters, which minimizes the residual sum of squares. For multivariate data, this method is not good at predicting the accuracy and interpretation of the model. In multidimensional problems, predictors are usually strongly correlated. Building a good model is a key element to achieve the desired effect, looking for a solution in the analysis of high-performance data. The work presents the elastoc net method, which causes rare solutions, encouraging the selection of a group where strongly correlated predictors are usually selected or rejected together. Ridge and LASSO regularization helps in choosing a possible solution. The elastic net method is a linear combination of L_1 and L_2 penalties. combining useful properties of ridge and LASSO regularization.

We are considering a linear regression model, where X is the predictor matrix and the ridge coefficients are defined as

(1) $$\hat{\beta}^{ridge} = \arg\min_{\beta \epsilon R^k} \|Y - X\beta\|_{L_2} + \lambda\|\beta\|_{L_2},$$

where $\|\beta\|_{L_2} = \|\beta\|^2 = \langle \cdot,\cdot \rangle$ is a scalar product, the tuning parameter λ has a positive value (λ>0).

Equation (1) has a unique solution. When it ranges from 0 to 1, it balances the two options: adjusting the linear y and X model and reducing the coefficients. Ridge regression allows you to reduce the coefficients to zero by imposing a L_2 penalty. It cannot accurately reset zero. It allows assign close coefficients to highly correlated variables, but it cannot perform a variable selection (for specific real coefficients that are exactly zero).

LASSO is characterized by several advantages combining ridge with a variable selection. We are considering a linear regression model where LASSO estimates are defined as

(2) $$\hat{\beta}^{lasso} = \arg\min_{\beta \epsilon R^k} \|Y - X\beta\|_{L_2} + \lambda\|\beta\|_{L_1},$$

where $\|\beta\|_{L_1} = \frac{1}{k}\sum_{i=1}^{k}|\beta_i|$ and λ>0.

LASSO causes some coefficients to be shortened to zero exactly because of the L1-penalty geometry. This method can select variables, which is essentially different from ridge regression. LASSO, however, has some limitations, it tends to choose only one variable from the group and it is not for this method which one is chosen.

Simulation research and real data show that elastic net often exceeds LASSO, encourages grouping effect, where strongly correlated predictors occur together in a given model or outside of it. The method is particularly useful when the number of predictors is much larger than the number of observations.

The problem of identification of linear dependencies is well known in the literature of the subject. Let us consider the problem of identification of dependence, which is described by the linear equation

(3) $$Y = X\beta + \varepsilon$$

where $Y \in R^n, X \in R^{n\times(k+1)}$ are the observation matrices of a dependent variable and independent variables respectively, $\beta \in R^{k+1}$ denotes the matrix of unknown structural parameters. In the state equation (3) the vector $\varepsilon \in R^n$ represents the external disturbances. We assume additionally, that the sequence $\{\varepsilon_t\}_{1\le t\le n}$ is a sequence of independent identically distributed random variables with normal distribution $N(0,\sigma^2)$. The classical least square method consists in determining the unknown parameters $\beta = (\beta_0, \beta_1, \dots, \beta_k)$. In the equation (3) by solution the task

(4) $$\min_{\beta\in R^{k+1}} \|Y - X\beta\|^2$$

If $\det(X^T X) \neq 0$, then from Gauss-Markov Theorem we obtain, that the best linear unbiased estimator of unknown parameters β is equal $\hat{\beta} = (X^T X)^{-1} XY$.

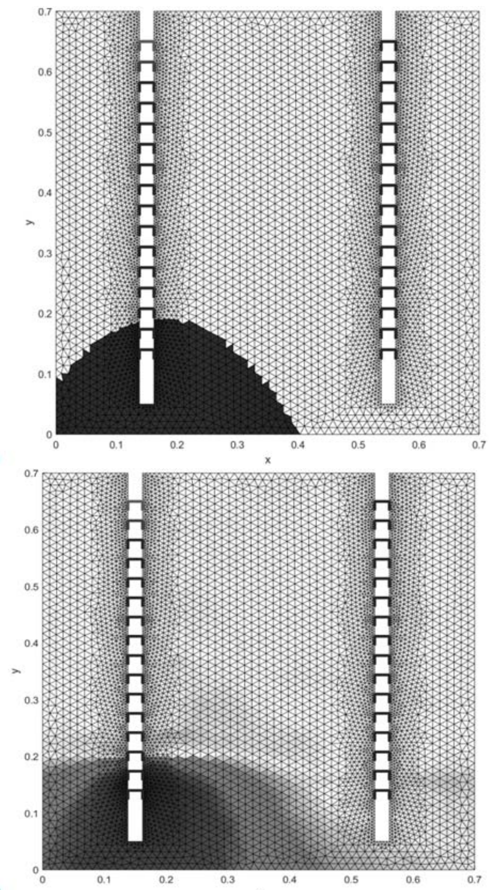
The elastic net method is a combination of ridge regression (called Tikhonov regularization, is one of the oldest methods of model regularization) and Least Absolute Shrinkage and Selection Operator (LASSO). The penalty function is described as linear combination L_1 and L_2 norms of unknown parameters in model (3). From above the penalty is defined as

(5) $$P_\alpha(\beta') = (1-\alpha)\frac{1}{2}\|\beta'\|_{L_2} + \alpha\|\beta'\|_{L_1} = \sum_{j=1}^{k}\left(\frac{1-\alpha}{2}\beta_j^2 + \alpha|\beta_j|\right),$$

where $\beta = (\beta_0, \beta')$ and $\beta' = (\beta_1, \dots, \beta_k)$, whereas $0 \le \alpha \le 1$. The unknown parameters in model (3) we determine by solution the task

(6) $$\min_{(\beta_0,\beta')\in R^{k+1}} \frac{1}{2n}\sum_{i=1}^{n}(y_i - \beta_0 - x_i\beta')^2 + \lambda P_\alpha(\beta'),$$

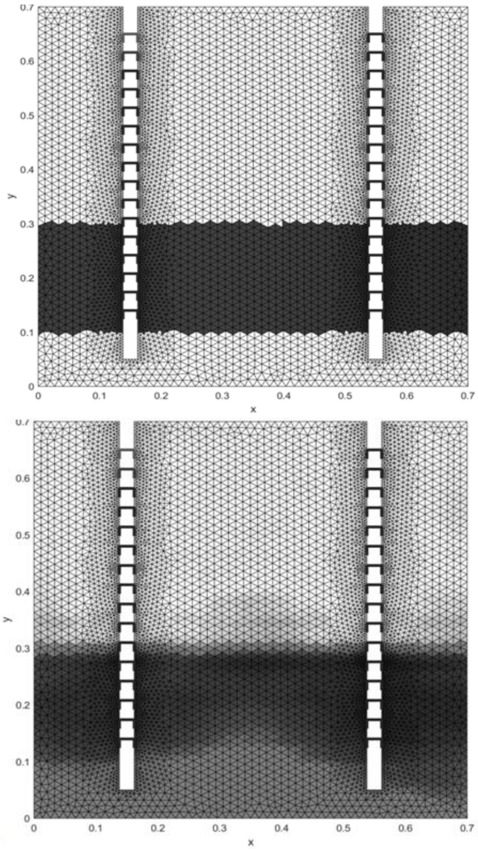
where $x_i = (x_{i1}, \dots, x_{ik})$ for $1 \le i \le n$, whereas the parameter $\lambda > 0$ defines the penalty coefficient.



(a)

(b)

Fig. 3. Model VII flood embankment with 1 multi-sensor electrodes – example I: (a) pattern, (b) image reconstruction



(a)

(b)

(b)

Fig. 4. Model VII flood embankment with 1 multi-sensor electrodes – example III: (a) pattern, (b) image reconstruction

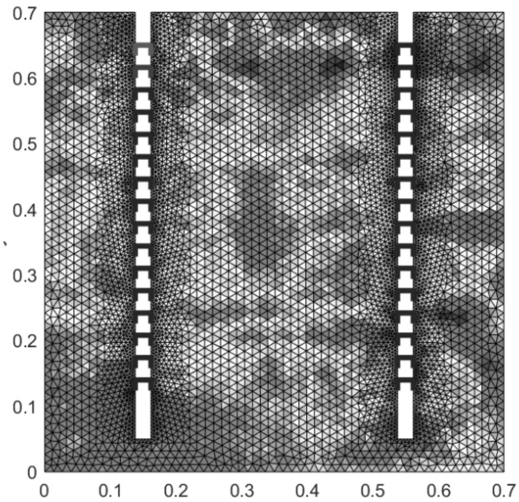


Fig. 5. Real reconstruction based on measurement data - model VII flood embankment with 2 multi-sensor electrodes

Results

The two-dimensional model shows a cross-section of the flood embankment with two multi-electrode sensors. All electrodes are placed on the rod and are deeply inserted.
Model parameters:

- number of nodes: 6112,
- number of triangles: 11404,
- number of electrodes: 2x16,
- type of electrodes: many sensors.

For two stimulation methods (stimulation 1 contains 896 measurements, stimulation 2 contains 448 measurements) the parameters of linear models were estimated using a flexible mesh. The results of the reconstruction are shown in Figs. 3 and 4. Experimental conclusions: the reconstruction depends on the data set. Figure 5 shows the results of image reconstruction based on real measurements using an electric tomography system.

Conclusion

The article presents the original concept of a flood embankment monitoring system, where a device, sessions and measurement models were developed to test problems with a flood embankment. The solution has been equipped with a multi-sensor electrode system based on tomographic measurements allowing for multiple measurements of electrical values, followed by appropriate analysis. Failure-related physical processes are often complex and cannot be measured accurately. The presented solution is an innovative approach because other methods cannot estimate changes or damages in the entire volume of the object. For the analysis of measurement data, the finite element method was used to solve a simple problem, and the elastic net method with ridge and LASSO regularization to solve an inverse problem. The learned algorithm works very quickly (the reconstruction time is a fraction of a second). The quality of the obtained images varies, when the object is in the middle or near the electrodes on the border of the domain shows the reconstruction with sufficient precision.

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