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Impact of the Radial Basis Function Spread Factor onto Image Reconstruction in Electrical Impedance Tomography ⋆

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Abstract: The major problem of the Electrical impedance tomography (EIT) is to get the resistivity distribution image of a given cross-sectional area. There are many methods solving this non-linear problem, mostly requiring certain simplifications and assumptions. Most of the methods are also computationally demanding and not easy to implement. The usage of the neural networks appears to be a solution of the mentioned problems. In this article we continued with our previous study and used Radial basis function (RBF) neural network for image reconstruction in electrical impedance tomography and we focused on examining how the change of the spread parameter of the RBF influences the result of the image reconstruction with the RBF neural network.

Keywords: Electrical impedance tomography, Radial basis function neural network

1. INTRODUCTION

Electrical impedance tomography (EIT) is a non-invasive imaging technique, which can be used to get the image of the cross-sectional area without any interventions into the human body. To gain image using EIT, the alternating electrical current of peak-to-peak amplitude value lower then $1mA$ and frequency ranging from $1kHz$ to $100kHz$ is applied onto the surface of examined object and appropriate voltage responds are measured, as described in (Michalikova and Prauzek (2014)). When using EIT imaging technique, one have to face the solution of both forward and inverse problem. The forward problem in EIT is in other words how to get voltage on the object's boundary corresponding to the distribution of impedance inside the object. Conversely, the solution of the inverse problem stands for how to estimate the inner impedance distribution from voltages obtained by measurement on the boundary of examined object - this stands for image reconstruction. The relationship between inner resistivity distribution and boundary voltages is determined by the Laplace equation and boundary conditions (Kim et al. (2001)).

There are several methods to solve the inverse problem, as described in (Wu et al. (2013)). Methods can be basically classified as linear, among which belong methods like Equipotential Backprojection, sensitivity matrix or regularization methods, and nonlinear methods (Newton – Raphson method and its modifications) (Wang et al. (2004)). These methods require certain simplifications and are computationally demanding (Adler and Guardo (1994)).

The Neural networks deployment for image reconstruction is a non-deterministic approach which can solve problems of other methods like computational demands, simplifying assumptions etc. It is commonly being used in various branches of biomedical engineering for example as described in (Prauzek et al. (2013)) and it has also been used in image reconstruction in Electrical capacitance tomography (Chen et al. (2012)) and in EIT (Wang et al. (2004), Wang et al. (2009a), Wang et al. (2009b)). In previous study(Michalikova et al. (2015)) we used Radial Basis Function neural network for image reconstruction. We continued in this study and in this article we deal with importance of spread parameter of RBF neural network and his impact onto results of image reconstruction.

2. ELECTRICAL IMPEDANCE TOMOGRAPHY

The goal of EIT is to map the inner impedance distribution ρ of an object Ω (which is considered as a volume conductor). As stated in introduction this requires the solution of forward and inverse problem. Mathematical model of EIT is described with generalized Laplace equation(equation 1) and boundary conditions (equation 2, 3)(Wu et al. (2013)):

$$\nabla \cdot \left(\rho(x,y)^{-1} \nabla \Phi\right) = 0, (x,y) \in \Omega \tag{1}$$

$$\Phi(x,y) = \Psi, (x,y) = \partial\Omega \tag{2}$$

$$\rho^{-1} \frac{\partial \Phi}{\partial n} = J_n, (x,y) = \partial\Omega \tag{3}$$

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whereas $\Phi(x, y)$ is electrical potential inside the Ω, $\rho(x, y) > 0$ is resistivity distribution inside the Ω object, n stands for outer unit normal vector to $\partial\Omega$, J_n is the electrical current density on the boundary and Ψ is potential on the boundary.

Forward problem solution comprises calculation of voltage that can be measured with electrodes on the surface for particular impedance distribution, whereas both the impedance distribution of given object and applied current value are known. The most common method to obtain numerical solution of EIT forward problem is Finite Element Method (FEM). The forward problem is modeled with Laplace equation and boundary conditions, as stated above. Using the FEM method, the region Ω is partitioned into a two-dimensional model of elements, which have a node in their each corner. There is an assumption that each of elements has its uniform resistivity (Xu et al. (2004)),

The a priori knowledge of the resistivity distribution and appropriate voltage on the boundary (meaning the numerical solution of forward problem) is essential for image reconstruction - the inverse problem. It was proved that the complete knowledge of the relationship between voltage and current at the boundary determines the inner resistivity uniquely (Holder (2005)). As it is well known, the solution of inverse problem in EIT is an ill-posed problem (Holder (2005)). To compute the resistivity distribution inverse problem solution uses the knowledge of current patterns and voltages measured on the boundary (Wang et al. (2009b)). There exist linear and nonlinear methods to solve the inverse problem, as stated in introduction.

In solution of inverse problem the applied current value and the voltage on the boundary, measured with electrodes are used to evaluate the estimated inner distribution of resistivity(Zhang et al. (2014), Wang et al. (2009a)).

3. RBF NEURAL NETWORK

A typical radial basis function network has three layers: (1) an input layer, (2) one hidden layer and (3) one output layer, see Fig. 1. Input layer can be considered as a vector of real numbers $x = (x_1, x_2, ..., x_J)$, where J represents the number of input elements. Each neuron in the input layer – input vector element x_j – is connected to each neuron in the hidden layer. The task of the input layer is only to pass the input signals to the hidden layer, there are no weights between the input and the hidden layer. The hidden layer contains a variable number of neurons N, whereas the optimal number of neurons is determined by the training process. Any of neurons in hidden layer comprises a nonlinear Radial Basis function as the neuron activation. Such a radial basis function, particularly the Gaussian function denotes equation 4 (Bishop (1995)).

$$\varphi_n(x) = e^{-\beta \, \|x-\mu_n\|^2} \tag{4}$$

where x is the input vector, $n = 1, 2, ..., N$, μ stands for prototype vector, $\|.\|$ denotes Euclidean distance and β stands for parameter, which controls the width of radial basis function.

It means that the activation of hidden–layer neurons is determined by the distance between the vector of inputs x and vector of prototypes $\mu = (\mu_1, \mu_2, ..., \mu_N)$ (Bishop (1995)). Each neuron can produce output signal in interval

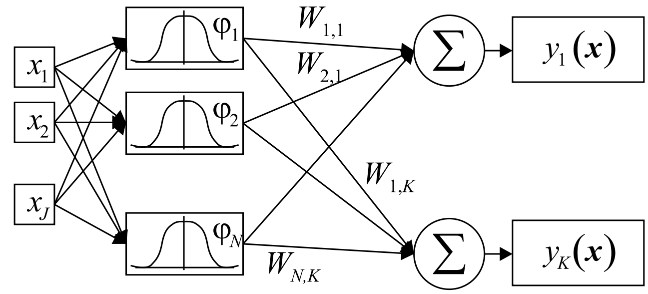

Fig. 1. Radial Basis Function network schematic

0 to 1, whereas the largest response of neuron (the value of 1) will be produced when the input to the neuron is equal to the prototype. Each element y_k of the output vector $y(x) = (y_1, y_2, ..., y_K)$ is a weighted linear combination of outputs of the hidden layer neurons as specifies equation 5 below.

$$y_k(x) = \sum_{n=1}^{N} w_{n,k} \cdot \varphi_n(x) \tag{5}$$

The RBF neural network is frequently exploited type of NN (Wang et al. (2004),Wang et al. (2009a)), since it has better approximation and classification ability and the learning of network is faster compared to other feedforward networks, as was pointed out in (Chen et al. (2012)).

4. INFLUENCE OF THE RADIAL BASIS FUNCTION SPREAD PARAMETER ON THE IMAGE RECONSTRUCTION

The objective of this study is to compare RBF neural networks with different spread parameter controlling the input area width to which each neuron responds and to asses the influence of changing this parameter onto image reconstruction. We used the same network design as in (Michalikova et al. (2015)).The RBF neural network was created and trained using Neural Network Toolbox in MATLAB. As network training data, we used EIDORS software (Adler and Lionheart (2006)) to create a set of Finite Element Method (FEM) based models of different resistivity distribution and to obtain boundary voltages. Properties of the RBF network are as follows: it has 928 inputs (input layer) and 3214 outputs (output layer), corresponding to number of elements in FEM model. Properties of the hidden layer were determined during network training by MATLAB Neural Network Toolbox: it has 100 neurons with radial basis transfer functions. The spread parameter – the input parameter into RBF network design controls the width of an area in the input space to which each neuron in the hidden layer responds. According to description in the chapter 3 it corresponds to β parameter. The larger β is, the larger number of neurons will respond to an input which is distanced of the β value from the prototype vector μ.

We have created and trained several RBF neural networks with different spread parameter, but due to lack of the space we compare two networks with β equal to 0.5 and 0.3 in this article.