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# Deep Learning in Development of Model-Dependent Diagnostic: Recognition of Detector Characteristics in Measured Responses

Miroslava Jordović Pavlović, Dragan Markushev, Slobodanka Galović, Marica Popović

***Abstract*— Deep learning has successfully been implemented in various domains, including photoacoustics. The collection and creation of massive datasets creates new possibilities. Deep learning methods, when applied on massive datasets, are able to extract very useful patterns. This can lead to solutions to many problems. In this paper we discuss and develop deep learning application for the recognition of a detector influence pattern on recorded responses of a measurement chain in model-dependent experimental measurements. This enables the fast calibration of the method, which is necessary for its further application in the characterization or scanning of the examined objects with satisfactory accuracy. Frequency gas-microphone photoacoustic measurements were taken as the case study. The paper presents three models for the solution of instrument influence on true signals in photoacoustic experiments. We analyze the influence of neural network depth and the number of outputs on the prediction accuracy, and then we discuss the choice of the optimal solution.**

***Index Terms*—Deep learning; regression; massive dataset; photoacoustics; model-dependent diagnostic; microphone.**

## I. Introduction

Deep learning is the area of machine learning which has seen the most intensive growth in the past few years. By bringing new techniques, algorithms and implementations, deep learning has produced impressive results. These methods have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection, and many other domains [1]. Generally, deep learning is applicable in many fields of science, medicine, business, and in other real-world problems. Deep learning algorithms can potentially be used in every field of medicine, from drug discovery to clinical decisions. In those applications, like many others, deep learning is far ahead of other machine learning algorithms. Deep convolutional networks have been proven as a good solution for medical image classification, localization, detection, segmentation, and registration [2].

Deep learning in bioinformatics has many applications: sequence analysis, biomolecular property prediction, biomedical image processing and diagnosis [3].

Another reason for the present and future successes of deep learning is that it requires very little engineering by hand, so it can easily take advantage of increases in the amount of available computation and data. Deep-learning methods are representation-learning methods with multiple levels of representation, obtained by composing simple but non-linear modules, each of which transform a representation at one level (starting with the raw input) into a representation at a higher, slightly more abstract level. With the composition of a significant number of such transformations, very complex functions can be learned. Methods may very well discover interesting structures in large datasets [1][4][5]. Those are the reasons why they are very suitable for application in many domains.

This paper will show that deep learning is applicable in model-dependent diagnostic techniques with no calibration method, which enables the exclusion of measurement chain influence and in particular the influence of the microphone characteristics. This influence is not at all simple and eludes the usual kinds of differential calibration and standardization on the referential sample. Having said that, characterization done by those methods cannot give the exact properties which could satisfy fundamental scientific research. The case study was carried out for gas-microphone frequency photoacoustic technique. Justification of deep neural network application in photoacoustics relative to shallow neural networks is presented.

## II. Deep Learning in Photoacoustics

Physical parameters that configure in the physical model of the photoacoustic response are mostly nonlinearly dependent, very often with unknown and unavailable characteristics of the transformation process of the examined physical quantity in the electric signal. It is expected that the development and application of neural networks in photoacoustics and all similar model-dependent methods which use detectors of a common purpose is a good decision because deep learning is able to

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approximate any nonlinear mapping with very high accuracy and reliability, and in that manner recognize and extract pattern of influence of individual parameters on true signal enabling calibration of the method. Also, classification models of different nonlinear mappings could be designed with very high accuracy using deep neural networks, which are applicable in the selection of different source influences on the true signal.

Neural networks are present in photoacoustics and other model-dependent measurement techniques which have been developed for scientific research and biomedical diagnostics for a very long time.

In [6], a shallow neural network is used for the reconstruction of the optical profile of optically gradient materials based on the frequency, magnitude and phase of the measured PT (photothermal) response.

In paper [7] shallow neural network with forward signal propagation was designed and used to simultaneously determine main physical parameters, such as: thermal diffusivity, thermal expansion coefficient and thickness, from transmission, frequency modulated photoacoustic response of the sample.

Examples of deep learning application in photoacoustics for the past few years are numerus.

Paper [8] presents deep convolutional network application for noise removal in photoacoustic recognition of images. Photoacoustic imaging is a method for the visualization of point-like targets. Using this method, detection of anatomical features or metal implants in the human body is possible, which can further be used in cancer detection, monitoring blood vessel flow, detecting and guiding surgeries, etc. Laser beam transmission in the presence of highly echogenic structures has consequences for the creation of a reflection artifact that may appear as a true signal. Deep convolutional networks turn out to be a good solution for the classification of a true signal from other artifacts with high accuracy and reliability.

A deep learning framework for image reconstruction in photoacoustic tomography (PAT) is presented in [9]. A sparse data problem is discussed. A direct and highly efficient reconstruction algorithm based on a deep convolutional neural network was developed. Neural network weights are adjusted prior to the actual image reconstruction based on a set of training data. The proposed reconstruction approach can be interpreted as a network that uses the PAT filtered backprojection algorithm for the first layer, followed by the U-net architecture for the remaining layers. Numerical results demonstrate that the proposed deep learning approach reconstructs images with a quality comparable to the state-of-the-art iterative approaches for PAT.

In [10] the authors used an MLP (Multy Layer Perceptron) for the simultaneous determination of the laser beam spatial profile and relaxation time of the polyatomic molecules in gases in real time within trace atmosphere gas monitoring. The spatial profile of the laser beam is variable, so its simultaneous determination contributes to the precision of the photoacoustic experiment, because it will correct the resulting variations. The same authors go a step forward in [11], so a feedforward MLP recognizes both the spatial profile of the laser beam and the values of the laser fluence, which contribute to additional precision in the measurement of different pollutant concentration in a wide range of values in a urban and rural environment.

However, as far as we know, neural networks have not yet been applied to the recognition of the influence of processes that are happening inside the detector. Data used for characterization are dependent on those processes. This influence cannot be understood as noise, but as a systematic influence which depends on the detector, and two completely identical detectors do not exist in practice. Accordingly, detector recognition is a kind of measurement set calibration, particularly in situations of detector changes when higher gain or a different measurement range is needed for different materials and structures or because of the failure of the existing detector in the serial measurements of the same sample. Such a calibration is a necessary step for a further inverse problem solution, apropos the determination of the examined sample characteristics with an accuracy required for fundamental research, which is significantly higher than the accuracy required for the application of some materials and structures or for biomedical diagnostics. In this paper the methods are based on deep neural networks which are able to effectively and very quickly recognize detector influence so that the calibration of the used experimental set can be done as suggested.

## III. MASSIVE DATASET REGRESSION MODELS FOR DETECTOR PARAMETER PREDICTION

Our aim is to incorporate computational intelligence, especially deep learning, in the so-called "intelligent measurement system", which will be able to perform complex commands. We expect that such a system will be able to learn and to adapt to specific problems and to maintain high accuracy, reliability, and measurement rate. In the beginning, our intelligent measurement system will have the possibility of signal autocorrection relative to instrument influence. Although the case study was done on gas-microphone photoacoustic frequency measurements, the method application can easily be extended to a great number of model-dependent measurement systems with variable detectors.

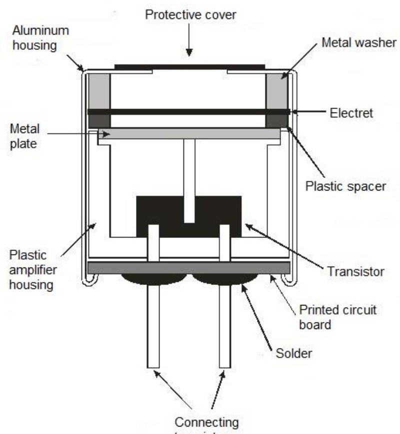


Fig.1. Schematic diagram of a cell of minimal volume.

We previously created a simple and cheap photoacoustic measurement device [12], Fig.1. The common characteristic of of experimental signals due to the electronic or acoustic properties of the used instruments in the frequency domain [13], Fig.2. Based on the analysis of a great number of executed measurements on different materials and a comparison with the theoretical predictions which assume the detector to be ideal, it can be concluded that the microphone as the basic part of the detector measurement system brings most of the disturbances into the experiment.

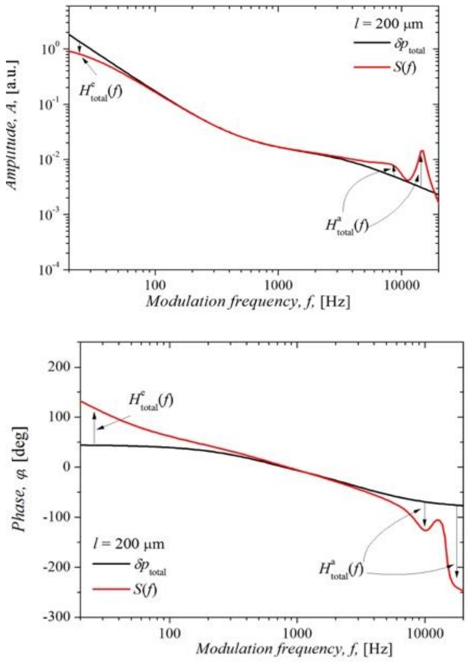


Fig. 2. Simulated a) amplitude and b) phase of the total photoacoustic signal (black line) and distorted experimental signal (red line)

A database of 67500 records was obtained from a well-known theoretical model. We obtained a massive dataset, and it is in precisely such datasets that deep learning recognizes interesting and useful structures, as well as patterns of non-linear dependence. The dataset was structured and labeled. The theoretical data corresponded to the commercial microphone ECM30B. Based on the statistical analysis of the collection of experimental measurements, it was concluded that frequency $f_2$ is the most stable one compared to the observed parameters, and three values were taken for network training: the central value 25 Hz and two values which are $\pm 5$ % of the central value (23,75 Hz and 26,25 Hz). Also based on the statistical analysis, it was concluded that 10 values should be taken for each of the frequencies $f_3$ and $f_4$, distributed at equal distances in the range 8930-9866 Hz and 13965-15432 Hz, respectively. The least stable parameters are the damping factors of the second order low-pass filter, and they were presented with 15 values which were irregularly distributed from 0.015 to 0.99. Some of the curves from this dataset are presented in Fig. 3 (2250 lines). Every curve is presented with 200 points, and every point is presented with two characteristics, an amplitude and phase. In this way, one record in the database is presented with 400 all photoacoustic measurement systems is the high distortion features, 200 amplitudes and 200 phases. The dataset was first shuffled and then divided into a training set of a total of 57500 records or 82.6% of the total number of recordings, a validation set and a test set both of 5000 records or 8,7% of the total number of recordings. In this way, the training, validation and test sets were obtained randomly.

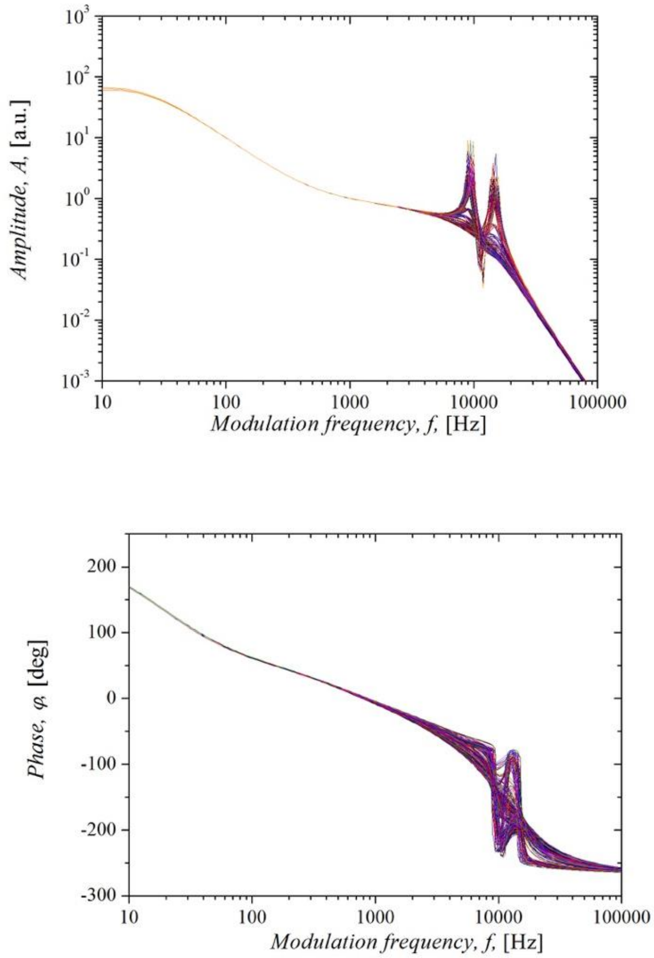


Fig.3. Curves: a) amplitude and b) phase of distorted photoacoustic signals with different microphone characteristics from the dataset used for network training [14].

Our aim is the development of a regression model for the prediction of five specific microphone parameters connected to its electronic and geometric features, which are not determined by the producers and could not be found in the specifications for the particular microphone. Based on our analysis of the theoretical models of the microphone as a sensor and a converter of pressure changes into an electrical signal, as well as those carried out on electrical measurements, it was shown that a five-parameter description of the detector influence on every detected signal is enough. In that way, microphone influence on the experimental signal can be determined. Now it is possible to correct the experimental signal in order to reach a "pure" signal, generated only from the excited sample. An MLP was our choice because of higher accuracy.

In this paper we present three regression models. The first model has an MLP with three layers, two of which are hidden, the first one with 30 neurons, and the other with 17 neurons, and one output layer with 5 neurons. The second model has 5 MLPs with three layers, two hidden, the first one with 30 neurons and the second with 17 neurons, and one output layer with 1 neuron. The third model has an ANN (Artificial Neural Network) with one hidden layer with 47 neurons, and is a shallow neural network. The network outputs represent the targeted microphone parameters: $f_2$, the characteristic microphone frequency connected to its RC characteristics, $f_3$, $f_4$ characteristic acoustic resonances of the microphone, and $\xi_3$ and $\xi_4$ reciprocal quality factors. The characteristics of a lock-in amplifier, whose role is played by the sound card described with parameter $f_1$, is considered known ($f_1$=15Hz). The input vector has 400 features, Fig. 4

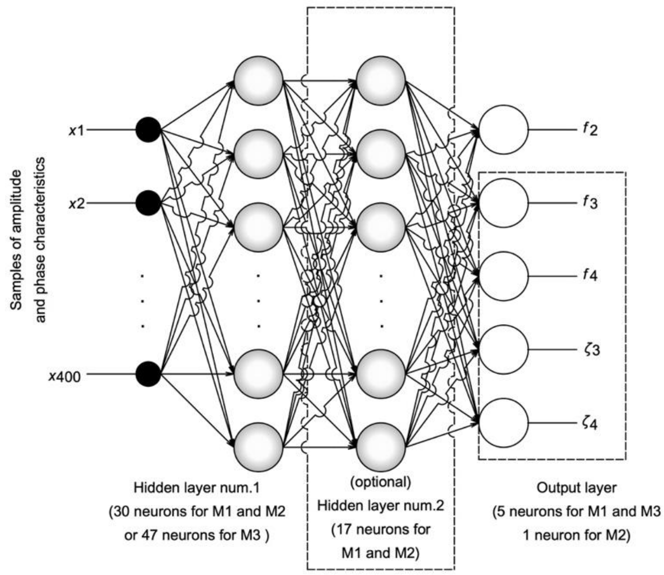


Fig. 4. Structure of Model1, Model2 and Model3

The normalization of the input vector was achieved by dividing each element $x_i$ of the input vector by the maximum absolute value, determined over all the examples at the "$i$" frequency. This normalization type proved itself as the best solution for our model, then some others. With the application of this normalization type and without a value change in the other parameters, an acceptable value for the accuracy of the model was obtained in the iterative process of model parameter selection. We tested two more types of normalization, normalization obtained by subtracting the mean value of all examples at the "$i$" frequency from each element $x_i$ and by dividing it by a standard deviation, as well as N2 or the Frobenius norm, but the results were not acceptable. The output vector $y$ is normalized in a similar manner.

We chose a tanh activation function and the Xavier algorithm for weight initialization. [15]

We applied supervised learning for the model training. The Adam algorithm for error function evaluation was applied in order to achieve optimal weight values in the backprop [16]. The optimization is intensified by the Mini-batch technique, which is applied when the dataset is big enough (as it is in this case). This technique provides visible results of parameter optimization even in the first epoch, thanks to the division of the given dataset into smaller ones, which are treated as a whole, and applies error function evaluation on these smaller datasets. The learning rate for all the models has the same value of $10^{-4}$.

The open source platform for machine learning, Tensorflow, was used for the realization of the models. Tensorflow is very popular for the realization of deep neural networks. It is based on a data flow graph. The graph nodes represent mathematical operations, while the graph edges represent the multidimensional data arrays (tensors) that flow between them.

Metrics for the models were defined, the same for all three models: deviation from the accurate value is less or equal to 5%, and that corresponds to the photoacoustic experiment. Model accuracy was analyzed relative to the set metric. The error function value on the training set and the validation set are similar, so we can conclude that model generalizes well and is not overfitted.

In accordance with Table1, it was concluded that the best results were achieved with Model 2, and the worst with Model 3. By dividing the same number of neurons into two layers, we got an accuracy approximately 2% higher in Model 1 than in Model 3. This difference will be bigger if the network is trained on experimental values, because theoretical models present idealizations, i.e. an approximation of real conditions. Is 2% small enough not to make a difference between the models? It depends on the application, for the photoacoustic experiment for industrial application it is significantly high. The importance of neural network depth for learning was proven by the increase of the accuracy of the model with more layers, under the same conditions (learning rate, number of epochs). Model 2 proves the fact that the deeper the neural network is, the better the recognition of behavior patterns in the data. Reducing the deviation from the accurate values in Model 2 in relation to Model 1 shows that the multilayer neural network can approximate the nonlinear output quite well. In Model 2 the neural network concentrates all its power on one output and achieves a very high accuracy for 3 of the 5 microphone parameters, as much as 99.99%, while training lasts for a far smaller number of epochs.

TABLE I:
A COMPARATIVE ANALYSIS OF THREE REGRESSION MODELS FOR THE PREDICTION OF THE MICROPHONE PARAMETER

| | Accuracy | | Cost | | Numbers of epochs |
|---|---|---|---|---|---|
| Model 1 | 98.59% | | 0.000001 | | 5000 |
| Model 2 | 99.99%,99.99%,99.99%,99.61%, 99.596% | | <0.000001,<0.000001,<0.000001,0.000001, 0.000001 | | 1500,1500,1500,3000,3000 |
| Model 3 | 0.969833 | | 0.000003 | | 5000 |
| Average deviation from the accurate value expressed in the percentage of the accurate value on the training set | | | | | |
| Parameter | $f_2$ | $f_3$ | $f_4$ | $\xi_3$ | $\xi_4$ |
| Model 1 | 0.02025029 | 0.08571574 | 0.03485037 | 1.0117933 | 0.59135133 |
| Model 2 | 0.00367374 | 0.04975093 | 0.02321718 | 0.44225055 | 0.28317332 |
| Model 3 | 0.03180477 | 0.1299281 | 0.06766562 | 1.9676312 | 1.1875261 |
| Average deviation from the accurate value expressed in the percentage of the accurate value on the validation set | | | | | |
| Parameter | $f_2$ | $f_3$ | $f_4$ | $\xi_3$ | $\xi_4$ |
| Model 1 | 0.02028082 | 0.08540299 | 0.03530468 | 0.998583 | 0.60733956 |
| Model 2 | 0.00359443 | 0.05007159 | 0.02289878 | 0.4521597 | 0.31682032 |
| Model 3 | 0.03162626 | 0.12913962 | 0.06732392 | 1.9448547 | 1.1696345 |
| Average deviation from the accurate value expressed in the percentage of the accurate value on the test set | | | | | |
| Parameter | $f_2$ | $f_3$ | $f_4$ | $\xi_3$ | $\xi_4$ |
| Model 1 | 0.02026834 | 0.0861348 | 0.0351213 | 0.9855594 | 0.5777709 |
| Model 2 | 0.0037558 | 0.04898341 | 0.02315352 | 0.45252872 | 0.2967481 |
| Model 3 | 0.03270168 | 0.13082047 | 0.06930758 | 1.9330658 | 1.2145972 |
| Prediction time | | | | | |
| | CPU time | | Computation_time(CPU +load time) | | |
| Model 1 | 14 ms | | 31 ms | | |
| Model 2 | 14 ms | | 5x30 ms | | |
| Model 3 | 12ms | | 29ms | | |

In Model 1 the neural network splits its power to the five outputs, so the accuracy of this model is smaller. The same MLPs in Model 2 for different microphone parameters achieve different accuracies. This difference is just more proof that the network approximates the real situation very well. Parameters $\xi_3$ $i$ $\xi_4$ are very unstable photoacoustic quantities which depend on many other parameters. The theoretical model is not able to approximate the parameters very well. The neural network discovered this instability in the data.

## IV. CONCLUSION

In this paper we discussed deep learning application in the calibration of model-dependent measurement techniques with nonlinear detector influence on the measured signal. Few examples of successful application were presented. The analysis of three regression models for microphone parameter predictions in photoacoustic experiments was presented. It was shown that higher accuracy was achieved by models with two hidden layer neural networks compared to a model with one hidden layer neural network, for the same total number of neurons. Based on this, it can be concluded that it is the depth, not the size of the neural network that matters. In the development of the regression model for the purpose of correcting the measuring chain influence in photoacoustic experiments, we selected a two hidden layer neural network structure, not one with more hidden layers, because the achieved accuracy was satisfactorily high. We accomplished the set metric. However, we intuitively know that models with a higher depth will be our actual research direction for some of future applications in model-dependent measurements, especially for the case of complex nonlinear dependences of input and output quantities.

For the purpose of a “smart” measurement system development, we chose Model 1 as the most practical solution for our needs. The application of this regression model for calibration of experimental set could be generalized on similar problems in other measurement or transmission problems. We consider Model 1 and Model 2 as the real choices relative to the given requirements.

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