COMPUTATIONAL INTELLIGENCE BASED METHOD FOR EFFICIENT CLASSIFICATION OF MICROPHONES

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Abstract: *This paper presents a new, improved classification method of microphones as photoacoustic detectors by applying computational intelligence algorithms combined with expert knowledge. The classification method is part of the procedure of calibration of model dependent diagnostic technics. Novelty is dimensionality reduction to one, two or three measurement points depending on the point position on the frequency axis and it was considered in the data preprocessing. It has been proven that the presented classification method is accurate, reliable and needs less time than standard classification procedures, enabling fast and the precise processing of photoacoustic measurement data. Special achievement refers to the experimental procedure, regarding reduction in the number of measurement points needed for classification in comparison to the number usually used in the standard measurement procedure of the photoacoustic experiment.*

Keywords: *measurement data processing, neural networks, Principal Component Analysis, dimensionality reduction, microphone.*

1. INTRODUCTION

Artificial neural networks (ANN) are very powerful tools for data pattern recognition and thus intelligent decision making. Their capability to learn on a large dataset, as well as high processing speed, make them very suitable for application in photoacoustic, as one of the methods in photothermal science, bringing significant improvements in: design of photoacoustic devices, noise removal, photoacoustic tomography image reconstruction, determination of physical parameters, etc. [1],[2],[3],[4],[5],[6],[7], proving the fact that ANN and especially deep learning is making major advances in solving problems that have resisted the best attempts of the artificial intelligence community for many years [8].

Research presented in this article as well as our previous work are directed to ANN application in photoacoustic measurement data processing [9][10][11]. Significant improvements are obtained, firstly in experimental set instrument influence reduction, then in the remarkable decrease of running time, reaching so-called real-time work, while preserving the basic requirements – that the measurements are reliable and accurate.

In open-cell configuration photoacoustic spectroscopy, used in the inverse determination of sample properties, the microphone with associated electronics and a phase-frequency (lock-in) amplifier plays a major role [12]. Open-cell configuration by default means putting the test sample directly onto the microphone entrance so that the microphone hole takes on the role of a photoacoustic cell. The measured PA signal in modulation frequency that ranges from 20 Hz to 20 kHz is distorted because of the presence of noise that originates from different sources and the significant influence of the measurement instruments, primarily the microphone, and especially at the ends of the frequency interval [13]. With the aim of correcting the photoacoustic response and obtaining the pure signal originating only from the excited sample, calibration of photoacoustic measurement has to be done. Thus, classification and characterization of the microphone as a photoacoustic detector are needed. Firstly, the microphone has to be classified and then characterized by the determination of its transfer function and characteristic filter frequencies.

For simplicity, the microphone is considered as the main part of the measurement system with the greatest impact on distortions [13]. In our previous research, recognition of the microphone characteristics, as well as microphone classification were successfully managed by neural network application in order to isolate and correct its deficiency [9][11]. The distorted experimental signal can be corrected taking into account obtained electronic and acoustic parameters of photoacoustic detector – microphone and thus improving inverse solving of the PA problem by expanding the frequency range and increasing precision.

Database of simulated experimental values was used in both regression and classification models [9][11], obtained by a known theoretical model. Every record is presented with 300 features, which are the amplitude and phase of the samples taken at 150 frequencies in the range from 20Hz to 20kHz. The database for the regression model has 67,500 records and was taken as a large dataset. A neural network was trained for the prediction of five targeted microphone characteristics. The model is proven to be of satisfying accuracy (98,5%) and reliability (maximum deviation of predicted microphone parameter from the accurate value is 0.8% in the case of independently simulated experiments that neural network has never seen) [9]. The microphone classification model was trained to recognize microphone type out of possible three [11]. The database for the classification model has 202,500 records. Performance of the model was highly satisfactory: accuracy is 99,99% and training last only 100 epochs. Results on real experimental values are presented in [10].

However, during different models testing on independent numerical experiments as well as real experiments [10] we noticed a few problems and possible solutions using artificial intelligence (AI) algorithms and expert knowledge. Namely, in order to better define amplitude characteristics in the frequency domain, a very big number of measurements points is needed and that is the main problem of photoacoustic measurements. Another problem is the different number of measurements from experiment to experiment. The number of measurement points depends on experimental conditions and the one who is performing the experiment. These problems make measurements very slow and tiring, but also make scientific collaboration difficult. Because of that, such a method that will maintain accuracy and reliability, but a bigger measurement speed needs to be found.

The idea is reduction dimensionality algorithm application, Principal Component Analysis (PCA) in the data preprocessing phase. Dimensionality reduction means a reduction in the number of neural network inputs, so instead of the vector dimension n, there is a vector dimension k on the neural network input, where $k < n$ [14] [15]. It is expected that less numerous measurement points will be needed by the application of PCA, which means a smaller number of neural network inputs, and so the simplification of the experimental procedure, also a speed up and automatization of the whole process of microphone classification and calibration in whole. At the same time, the problem of a different number of measurement points from experiment to experiment is generalized. The application of the suggested method generalizes the choice and number of measurement points.

The goal of this paper is to discuss the minimum number of measurement points, namely the minimum neural network input vector dimension necessary for accurate microphone type prediction using AI algorithms combined with expert knowledge.

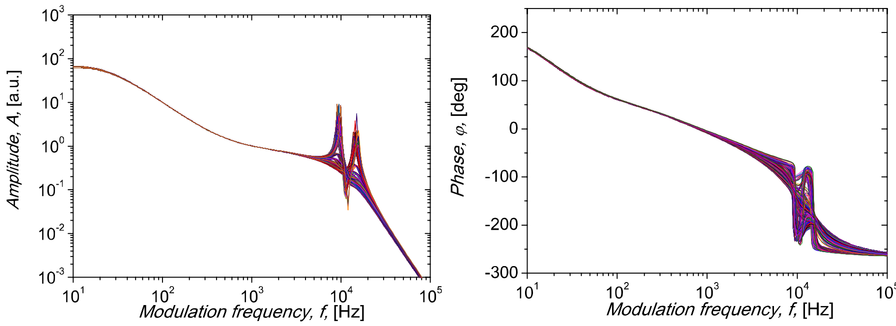

Figure 1: Curves a) amplitude and b) phase of distorted photoacoustic signal built upon the 2 500 records of the dataset used for network training for microphones: EMC30B, EMC60 and WM66 [9]

Studying responses obtained by various microphones that we found in the literature or managed in the experiments done by us, it can be concluded that relative to microphone behavior, frequency range from 20 Hz till the end of the interval of interest (20 000 Hz) can be separated in the tree subranges: low frequencies (<800Hz), flat subrange (800-2000 Hz) and high frequencies (>2000 Hz). Figure 1 proves those tree subranges in the case of shaped responses of tree electret microphones ECM30B, ECM60 and WM66. When it comes to microphone type, according to Figure 1, it can be obviously recognized at a low-frequency range. Microphone classification can be done at this part of the frequency interval. At flat subrange, amplitude overlap exists for all types of microphones. The overlap makes impossible a conclusion about the microphone type by simple response analyses. High-frequency subrange is also not suitable for classification by observation because microphone response depends on a lot of parameters (geometry of the system and detector itself, measured signal level, etc.).

In the further course of our research, expert knowledge about microphone behavior in the combination of AI algorithms will be used for feature selection, so the new classification method presented in this article is relative to frequency range and number of experimental points. Special attention is paid to parts of the frequency range where classification is not unambiguous enough based on standard analyses of amplitude-phase characteristics.

2. METHOD

The method consists of two procedures, firstly PCA has applied separately on each frequency subrange. Then relative to the frequency subrange the neural network is trained using a corresponding, the reduced dataset for classification of microphone type. So, the decision about the microphone type is obtained by information from only one subrange.

The designed neural network has three layers, Figure 2, two of which are hidden, and one which is an output layer. There are 25 neurons in the first hidden layer, 12 neurons in the second, and 3 neurons in the output layer. The design of the neural network and hyperparameter tuning as well as the creation of the dataset used for training are presented in our previous work [11]. The input vector presents samples of amplitude and phase characteristics of the analyzed microphone in a definite number of points on the frequency axis. The number of points is subject to further discussion in this paper. Three microphone types ECM30, ECM60 and WM66 are presented with three classes (0,1,2). Those classes are network outputs. At the same time, only one output can be of value 1, the other two are of value 0, meaning that the observed microphone belongs to the selected class (output=1).

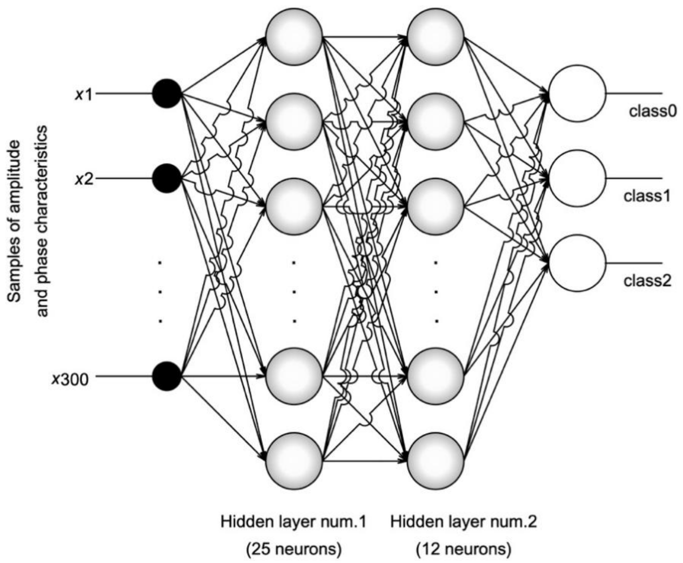

Figure 2: Neural network design: input-linear-tanh-liner-tanh-linear-tanh-softmax [11]

The number of features is the number of inputs of the neural network. One sample presented with amplitude and phase is the result of a one-point measurement, so the number of measurements is one half of the required number of features. Numerically, a one-point measurement is idle, but regarding principles to physics, the minimum for curve definition is five points.

4. RESULTS AND DISCUSSION

Based on the analysis of the estimated variance of the whole dataset (300 features) obtained by the PCA technique, it was concluded that the idea for dimensionality reduction of the input vector is completely justified, Figure3. The retained variance for 2 parameters (1amplitude + 1 phase), which means a reduction in the dataset dimension to only one measurement point at the frequency axis, is 99.67%. Variance for 4 parameters, meaning dataset dimensionality reduction to two points on the frequency axis, is 99.89%. Variance for 10 parameters, meaning dataset dimensionality reduction to five points on the frequency axis, is 99.98 %.

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According to the fact that a retained variance of 99% means not much loss of information at a reduced dataset and that variance values of 95-99% are optimal too [18][19][20], a performance analysis of microphone classification with one, two or three points on the frequency axis was performed. Additionally, experts conclusions about different microphone behavior depending on the part of the frequency range are taken into account. For that reason, the PCA algorithm is applied at each subrange separately.

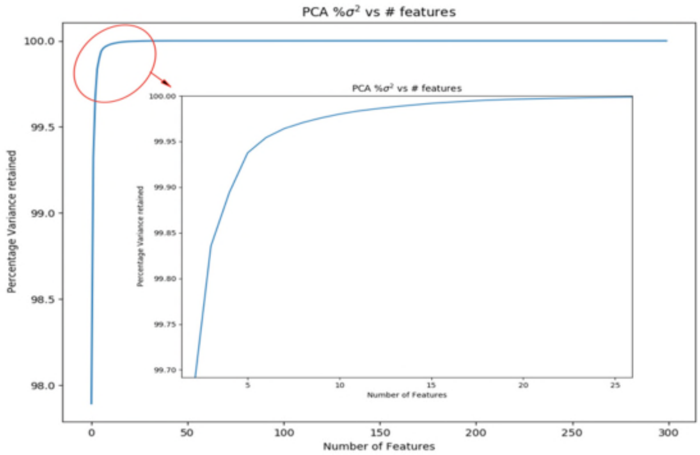

Figure 3: Reduced dataset variance depending on the number of features, analyzed at the whole range (20-20000) Hz

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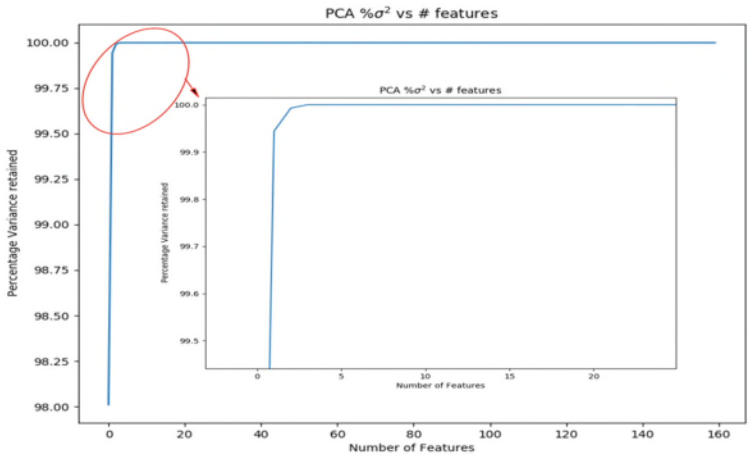

Figure 4: Reduced dataset variance depending of the number of features, analyzed at the NF subrange

The estimated value of variance by the PCA technique on the subrange of low frequencies is shown in Figure 4. This subrange has 160 features initially in each record, apropos 80 measurement points. For 2 features, meaning dataset dimensionality reduction to one point on the frequency axis, the variance has a value of 99.9929%. The value of variance for 4 features, meaning dataset dimensionality reduction to two points on the frequency axis, is 99.999998%. It is concluded that the analysis of microphone classification in this part of the range with only one point is completely justified.

The value of variance is 99,99993 %, estimated by the PCA technique at a flat subrange for 2 features (Figure 5). The value of variance for 4 features is 99.99999998%. The analysis of microphone classification for this subrange has been performed with one and with two points for a comparison of the results. The dimension is reduced from 40 to 2 and from 40 to 4 features in the second case.

The estimated variance using the PCA technique at the VF subrange for 2 features is 99.35 %. The variance for 4 features is 99.78 % and for 6 features is 99.88 %, Figure 6. The analysis of microphone classification for this subrange has been performed with two and with three points. The dimension is reduced from 100 to 4 and from 100 to 6 features in the second case.

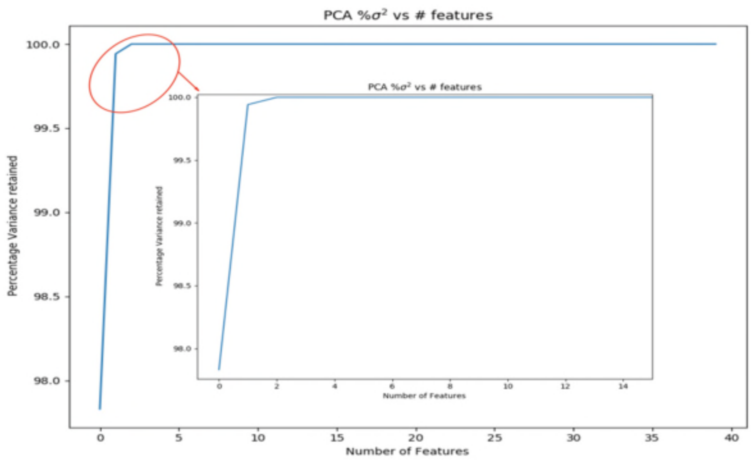

Figure 5: Reduced dataset variance depending on the number of features, analyzed in the flat subrange

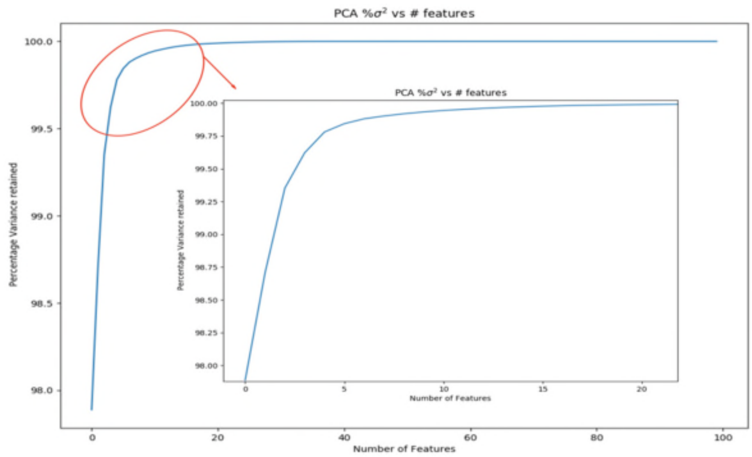

Figure 6: Reduced dataset variance depending on the number of features, analyzed in the VF subrange

The neural network is trained for each observed dataset separately, and the number of neural network inputs corresponds to the number of features in the record, apropos the number of measurement points. The results of the analysis are showed in Table 1, classification accuracy is given for the train, validation and test set separately. The duration of training is given as the number of epochs in the training.

Based on Table 1, it is concluded that our model is accurate enough in microphone classification in all three subranges. The best results for the corresponding subrange are shown in the following table.

Table 1: Model performance for each subrange

Frequency range	Retained variance	Number of points	Accuracy (train, dev, test)	Number of epochs
20-800 Hz	99.9054%	1	99.99%, 99.99%, 99.99%	100 epochs
800-2000 Hz	99.9889%	1	98.09%, 98.06%, 98.31%	3000 epochs
800-2000 Hz	99.99997%	2	99.99%, 99.99%, 99.99%	100 epochs
2000-20000 Hz	90.226%	2	67.44%, 67.5%, 66.5%	3000 epochs
2000-20000 Hz	95.3064%	3	99.91%, 99.87%, 99.93%	3000 epochs

The model is trained to classify microphones in the NF subrange with only one measurement point in high accuracy. Training time is very short, just a few minutes or if we measure time in epochs, it lasted 100 epochs. Such a good classification model performance proves that microphone characteristics at this subrange are reliable. That reliability was the basis for the model to train weights, which are used for very precise microphone type prediction for the suggested three. This conclusion fully corresponds to the current knowledge about microphone behavior in the NF subrange – in the NF subrange, RC microphone characteristics are dominant. Those characteristics are strictly defined and do not depend on experimental conditions.

The situation is a little bit different in the flat subrange, the model is less accurate with one measurement point than the model in the NF subrange with one point, but still, it is a good result. The training lasted longer than the training in the NF subrange under the same conditions. It can be concluded that microphone parameters are less reliable in this subrange than in the NF subrange. The reliability of the microphone parameters decreases with increasing frequency. The gained NF subrange model accuracy will be achieved in the VF subrange with three measurement points and with 3000 training epochs. This result points to the least reliability of microphone parameters in this subrange. This conclusion obtained from the presented model results corresponds to the theoretical facts too, that the microphone acoustic response is dominant in this frequency subrange, that its parameters are very unstable because of their dependence on microphone geometry as well as on the experimental conditions[21].

5. CONCLUSION

This paper presents a microphone classification model built using computational intelligence algorithms and expert knowledge. The goal of this research was not the classification of a sequence of microphones, but principally the presentation of a new classification model. The database of simulated experimental data is related to three types of electret microphones, which are commonly used in PA in a frequency range of 20Hz to 20KHz. The classification model could be easily extended to recognize more microphone types if such experimental requirements exist.

The analysis was performed in three subranges: NF (20-800Hz), flat (800-2000Hz) and VF (2000-20000Hz), because of the difference in microphone behavior in those three segments by expert opinion. This different behavior has been proven by the difference in the performance results of the presented classification model.

The model has satisfactory accuracy, with a maximum accuracy of 99.99% in the NF subrange. It works in real-time mode.

The main contribution of this research is the discussion on the minimum required number of measurement points for a precise microphone classification. In order to make a unique attitude, considering all three subranges, it can be concluded that the model needs only three points for microphone type prediction. That is a very good result compared to standard classification methods but is less than the needed number of points (5) if we didn't consider division on frequency subranges. Also, this way the problems of numerous measurement points and slow measurements are solved. The calibration procedure is improved, microphone characteristics can be obtained quickly, reliably and very precise.

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