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A method for efficient classification of microphones based on expert knowledge and computational intelligence

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ABSTRACT

Classification of microphones as photoacoustic detectors is important part of procedure of photoacoustic measurements calibration. The requirements of photoacoustic experiment are accuracy, precision, reliability and work in real time in order to be competitive measurement technique. According to current state, real time is still a problem. This paper suggests improvement of classification method currently in use by dimensionality reduction of input vector considered in the data preprocessing, having consequence in significant simplification of measurements and thus notable decrease of measurement time, so reaching real time calibration procedure. By applying the method presented in the article the number of measurement points will be one, two or three depending on its position on frequency axes which is extremely smaller number than commonly accepted (usually 70 - 80 for the frequency range 20 Hz - 20 000 Hz). The method is based on computational intelligence algorithms and expert knowledge.

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1. INTRODUCTION

Machine learning algorithms and especially neural networks are living extreme growth in number of applications, and their utilization in photoacoustic (PA) has been current trend, bringing significant improvements in: determination of physical parameters [1] [2] [3], PA instruments composition [4], noise influence decrease [5], PA tomography image reconstruction [6], etc. Literature overview brings a fact that deep learning is more and more represented in PA, what is understandable concerning the reality of deep learning, as most sophisticated artificial intelligence (AI) architecture [7].

Photo acoustics, as one of photo thermal methods, is an indirect measurement technique with the aim of determination of physical properties (thermal, optical, mechanical, elastic, electronic and others related ones) of the examined structure from its PA response. Mathematically, it is taken for inverse problem. In presented experiment inverse solution of inverse problem is applied meaning determination of physical properties of the sample based on measured photothermal response, developed mathematical model and well known preset of input parameters (the intensity and modulation frequency of the incident optical radiation) [8] [9]. The role of PA detector in the experiment has microphone with the associated electronics. Commonly, PA response is distorted as a consequence

of presence of noise and measurement instruments influence, microphone at first place. Distortions are especially prominent at the ends of frequency interval. The correction procedure is required [10], and thus calibration of PA measurement. The calibration in this case means classification and characterization of the microphone, resulting in isolating and correcting its deficiency. Firstly, the microphone should be classified among different types, frequently used in PA experiment. Then, microphone characterization is needed, regarding its transfer function and characteristic parameters. Classification and regression model are previously created based on artificial neural networks where the input vector is PA experimental signal [10] [11] [12]. Having applied the mentioned models process of calibration was upgraded in terms of precision and automatization.

Established PA practice is to use a very big number of measurements points (usually 70-80 for the frequency range 20 Hz - 20 000 Hz), because of better definition of amplitude characteristic and thus the input vector of mentioned classification and regression models has the same number of features. Although, multilayer perceptron and especially deep learning are not so sensitive to a big number of input vector features [7], these obstacles do not concern neural networks but are limitation in terms of time for measurement procedure itself. Its slowness specifically is the reason for the real time constraint. Moreover, experimental conditions and the one who is carrying on the experiment determine the exact number of measurement points. So, the number of measurements differs from experiment to experiment, and thus scientific collaboration is aggravated. Having all these facts in mind, the method which preserves accuracy and reliability, but also decreases measurement time and simplifies whole procedure is necessary.

The paper suggests novelty in choice of measurement point number and position on frequency axes. Dimensionality reduction of classification model input vector in preprocessing phase and expert knowledge are coupled to determine minimum number of measurements necessary for accurate microphone type determination. Less numerous measurements points are anticipated which causes a significant decrease of measurement time.

2. DESCRITPTION OF THE METHOD

Microphone response in the frequency and time domain differs due to construction, applied geometry and membrane type. Because of the difference in response, non-uniform phase and frequency response occur, presented in the literature as filtering [13]. EMC30B, EMC60C and WM66 are electret microphones commonly used in our PA experiments. At low frequencies (< 1 kHz), electret microphones behave as high-pass filters, while at high frequencies (> 1 kHz) these microphones usually act as acoustic low-pass filters [17]. Signal deviations both in amplitude and phase characteristics are present and especially noticeable at the ends of frequency range, which is indicated to a particular microphone type, Figure 1.

Microphone response variability recognition is the subject of many studies, with the aim of removing its influence and also overall measurement system, which will consequently increase the measurement range.
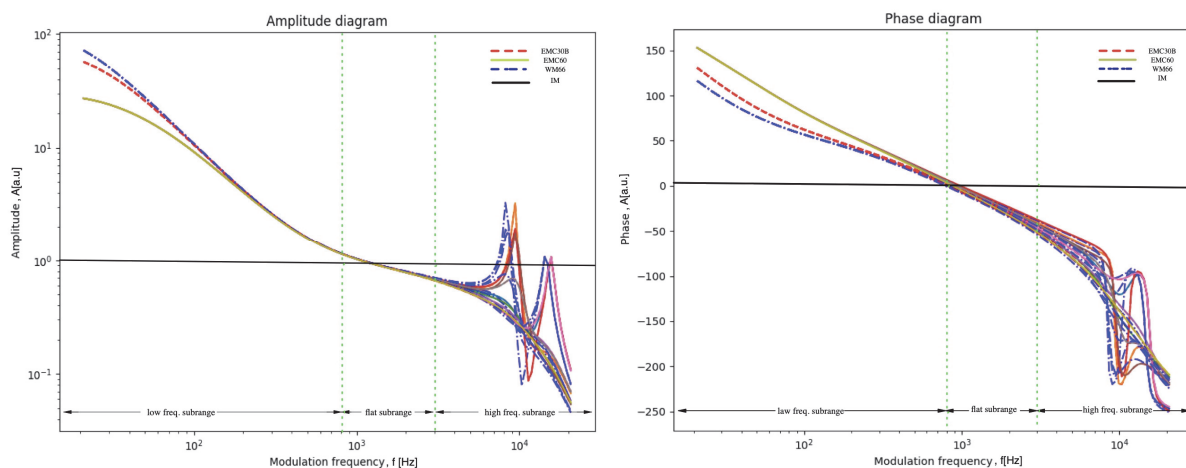

Figure 1: Distorted PA signal a) amplitude and b) phase characteristic. Curves belongs to a training dataset of classification model.

In our analyses, the unchangeable part of the experimental set is the lock-in amplifier with the other electronic devices needed for PA measurements, while the changeable part of the set is the microphone. The influence of the lock-in was considered to be known and its frequency was not changed while the influence of the other electronic devices was assumed to be negligible. Figure 1 illustrates amplitude and phase characteristics of distorted PA signal. Curves belongs to a training dataset of classification model. Each curve that belongs to the particular microphone type has different values of the characteristic microphone parameters: f_2 characteristic microphone frequency connected to its RC characteristics, f_3 and f_4 characteristic acoustic microphone resonances, ζ_3 and ζ_4 reciprocal values of the quality factors.

The method for dimensionality reduction presented in the article relies on expert knowledge and AI algorithms, and suggests the number of measurement points depending on the point position on frequency axes.

Considering experimental experience with PA responses of various microphones as well as permanent literature studying experts suggest splitting frequency range of interest (20 Hz - 20 000 Hz) relative to microphone behavior in three subranges: low frequencies (<800Hz, LF), flat subrange (800-2000 Hz) and high frequencies (>2000 Hz, HF). The explanation is - at low frequencies, deviations are consequence of microphone RC characteristics. At high frequencies, the microphone acoustic response is dominant. It is characterized by resonant peaks, which do not always appear and their intensity is not often the same because of huge variability in microphone acoustic response.

Curves originating from all types of microphone, overlap at flat sub rage, so here classification of microphones by observation is not possible, Figure1. Similar case is at high-frequency subrange, where the obstacles are microphone response dependency to a lot of parameters including system geometry, detector itself, measured signal level, etc. However, the situation is different at low frequency range, where microphone type could be clearly recognized, meaning that here microphone characteristics are dependable, determined and are not influenced by the experiment. Microphone parameters are the most reliable at NF subrange comparing to two other subranges. Microphone IM, illustrated at Figure 1 is microphone of ideal characteristics, used here as a reference.

The idea presented in the paper is microphone classification using information acquired either in NF, flat or HF range. It will be needed fewer measurement points and all of them will be located on same frequency range. The goal is to define the number of measurement points in each subrange. The method consists of two procedures. Principal component analyses (PCA) will give the sense about the minimal necessary dimension for every subrange separately. Finally, the decision about the number and position of measurement points at observed subrange will be made concerning expert opinion and accuracy of the model. PCA reduced set of components is not suitable as data in this case because PA measurement procedure needs precious determination of measurement point, so PCA will be used to give the sense about dimensionality reduction.
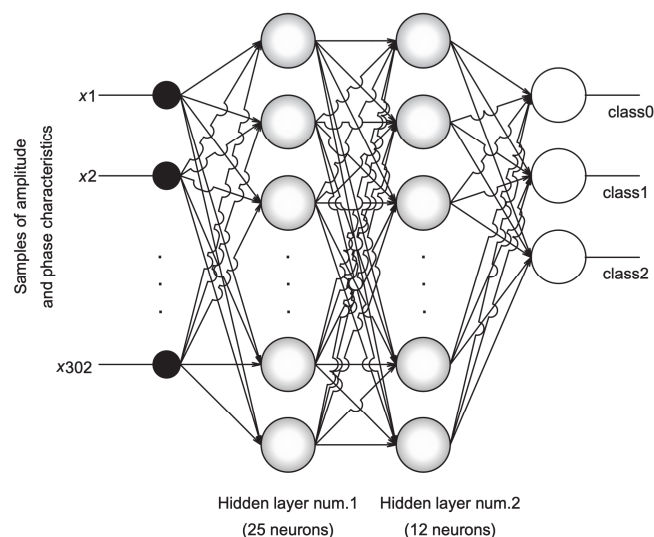

Figure 2: Architecture of the classifier [12]

In our previous work [12], classification model for microphone type recognition was developed based on neural network. Its architecture is illustrated at Figure 2. PA response sampled at 151 instances of amplitude and 151 instances of phase is model's input. Sample presented with amplitude and phase is the result of a one-point measurement, so the number of features is twice bigger then the number of measurement points. Output vector has three parameters as three microphone types, EMC30, EMC60 and WM66, labeled as (0, 1, 2) classes. Only one output can be of value 1 for particular input vector, selecting microphone type which corresponds to observed input.

3. RESULTS AND DISCUSSION

PCA applied on whole dataset (302 features) provides promising results of retained variance. Such a high value justifies the idea of dimensionality reduction of input vector. It means that the dimensionality reduction could be done even to 2 components, where retained variance is 99.67%. Results for 4 and 10 components are 99.89%, 99.98% respectively.

The retained variance of 99% means preserving information at a reduced dataset and observed reduction is set as a suitable dimensionality reduction [14] [15] [16]. Values of 95-99% are acceptable too. These facts were established as limiting parameters for proposed dimensionality.
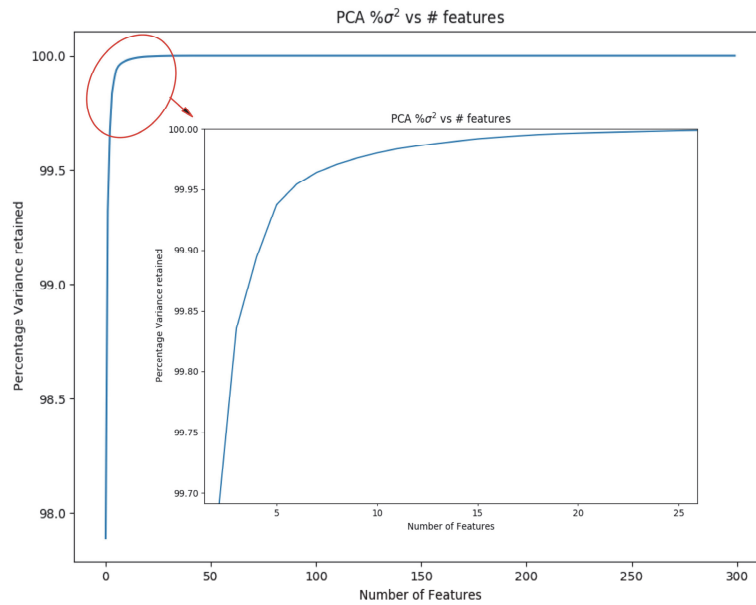
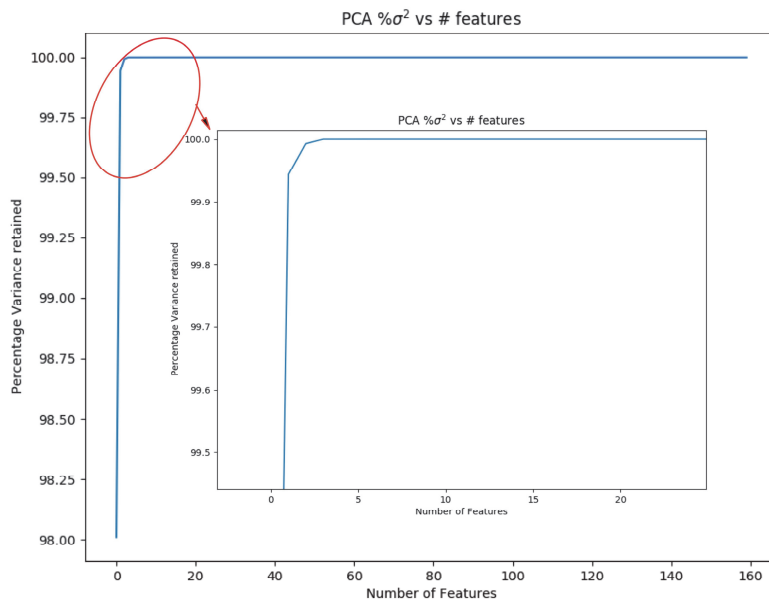Figure 3: Retained variance depending on the number of components, concerning whole range (20-20000) Hz

Figure 4: Retained variance depending on the number of components, concerning LF subrange

Figure 4 depicts results of PCA technique applied on LF subrange. 99.9929% is the variance of reduced dataset to 2 components and 99.999998% for 4 components. The initial number of features is 160 or 80 measurement points. Having in mind previously expert discussion concerning this subrange and limiting parameters microphone classification will be performed with two features input vector.

Figure 5 shows results of PCA technique applied on flat sub range 99,99993%, is the variance of reduced dataset to 2 components and 99.99999998%. for 4 components. The initial number of features is 40 or 20 measurement points. For the reason of results comparison classification will be performed in two cases, with two features and four features input vector.

In the case of HF subrange retained variance for 2 components reduction is 99.35 %, for 4 components is 99.78 % and for 6 components is 99.88 %, Figure 6. Microphone classification will be performed with two and with three measurement points, meaning dimensionality reduction from 102 to 4 or from 102 to 6 features.
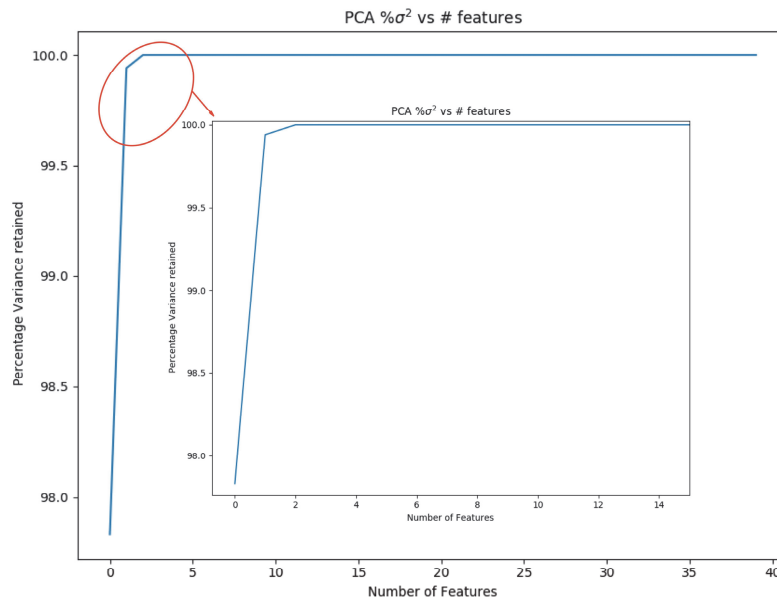
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Figure 5: Retained variance depending on the number of components, concerning the flat subrange
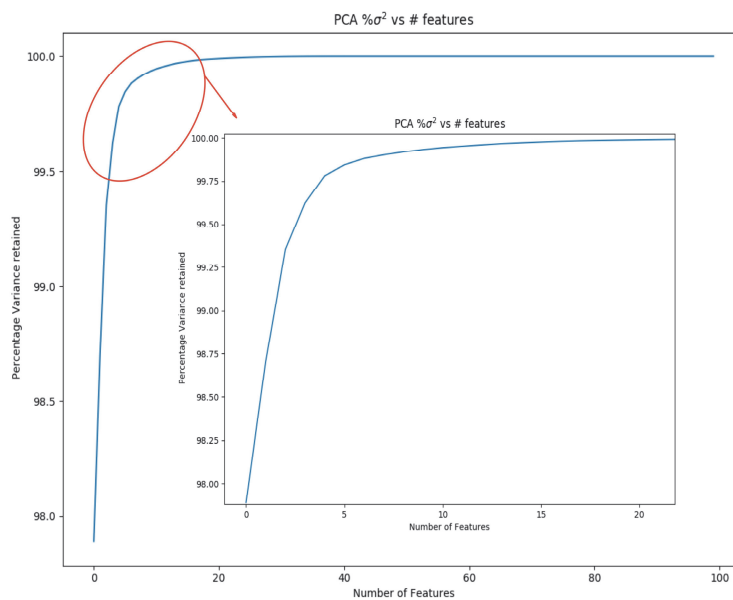

Figure 6: Retained variance depending on the number of components, concerning the HF subrange

The neural network is trained for each observed dataset separately. Table 1 presents the results of the analysis. It can be concluded that in each case train, dev and test accuracy are of similar values, so there is no overfitting nor bias. Classification is accurate enough with the exception of HF sub range with 2 measurement points.

Classification model for implementation in LF subrange has high accuracy where the input vector has two features obtained with only one measurement. Training lasted 100 epochs or a few minutes. Such a good result proves the dominance and reliability of the microphone RC characteristics at this subrange as experts pointed out.

Concerning flat subrange two analyses were done, training with one or two points. Accuracy of the model is high for both of the cases, but training for the case of two measurement points is significantly faster than with one point. Again, the performance of neural network corresponds to expert knowledge: microphone parameters are less reliable in flat subrange than in LF subrange. Although the time is of crucial importance in this research, model with two features input vector is chosen as classifier in flat subrange.

Expert opinion addressing HF subrange completely matches the performance of the analyzed models. Model with 4 features input vector (2 measurement points) has unsatisfactory accuracy while model with 6 features input vector (3 measurement points) has satisfactory accuracy and training time much longer then training time of excepted models for LF and flat subrange. The least reliability of microphone parameters in this subrange prove the dominancy of the microphone acoustic response in the subrange, which is unstable because of its dependence on

microphone geometry as well as on the experimental conditions. Having in mind all the facts: measurement time, training time and the rare experimental usability of the HF subrange model with 6 features input vector is chosen as classifier at HF subrange.

Table 1: Performances of the models

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

Adopted practice in designing machine learning models in our researches is testing new models on independent datasets separately created comparing with training database. For each type of microphone, five different numerical experiments for all of three subranges were made, where microphone parameter values are different but in the given parameter range. All 5 parameters f_2, f_3, f_4, ζ_3 and ζ_4 were changed in the theoretical model, obtaining Test1. The modulation frequencies f_2, f_3, f_4 are different, while the values of ζ_3 and ζ_4 are the same in Test2. In contrast, for creation of Test3, ζ_3 and ζ_4 are different, while the values of f_2, f_3, f_4 are the same. In Test 4 only f_3 and ζ_3, were changed and in Test 5 only f_4 and ζ_4 were changed. Table 2, illustrates the results of independent tests. Neural network classification represents the neural network answer about the type of microphone. Accuracy represents the success of neural network classification, whether the network classification matches the real microphone type or not. ECM30B is presented with class 0, ECM60 is presented with class1 and WM66 is presented with class 2.

Based on Table 2, it was concluded that the model interpolates outputs well because the prediction accuracy for unknown values of the microphone parameters in all three subranges is 100%. This proves the reliability of the pre-sented classification models, and overall method for efficient classification of microphones as detectors in PA experiments. Prediction time satisfies the real time concept and is considered as the time the network needs for the calculation of output parameters for a given input vector. Time for the load of weights from the external memory was not considered.

Table 2: Independent numerical experiments testing

Classification with a point at the LF subrange, microphone type ECM 30B					
Applied test	Test 1	Test 2	Test 3	Test 4	Test 5
Neural network classification	0	0	0	0	0
Accuracy	✓	✓	✓	✓	✓
Classification with a point in the LF subrange, microphone type ECM 60					
Applied test	Test 1	Test 2	Test 3	Test 4	Test 5
Neural network classification	1	1	1	1	1
Accuracy	✓	✓	✓	✓	✓
Classification with a point in the LF subrange, microphone type WM66					
Applied test	Test 1	Test 2	Test 3	Test 4	Test 5
Neural network classification	2	2	2	2	2
Accuracy	✓	✓	✓	✓	✓
Classification accuracy with a point in the LF subrange: 100%. Prediction time 17ms.					

Classification with two points in the flat subrange, microphone type ECM 30B					
Applied test	Test 1	Test 2	Test 3	Test 4	Test 5
Neural network classification	0	0	0	0	0
Accuracy	✓	✓	✓	✓	✓
Classification with two points in the flat subrange, microphone type ECM 60					
Applied test	Test 1	Test 2	Test 3	Test 4	Test 5
Neural network classification	1	1	1	1	1
Accuracy	✓	✓	✓	✓	✓
Classification with two points in the flat subrange, microphone type WM66					
Applied test	Test 1	Test 2	Test 3	Test 4	Test 5
Neural network classification	2	2	2	2	2
Accuracy	✓	✓	✓	✓	✓
Classification accuracy with a point in the flat subrange: 100%. Prediction time 17ms.					
Classification with three points in HF subrange, microphone type ECM 30B					
Applied test	Test 1	Test 2	Test 3	Test 4	Test 5
Neural network classification	0	0	0	0	0
Accuracy	✓	✓	✓	✓	✓
Classification with three points in the HF subrange, microphone type ECM 60					
Applied test	Test 1	Test 2	Test 3	Test 4	Test 5
Neural network classification	1	1	1	1	1
Accuracy	✓	✓	✓	✓	✓
Classification with three points in the HF subrange, microphone type WM66					
Applied test	Test 1	Test 2	Test 3	Test 4	Test 5
Neural network classification	2	2	2	2	2
Accuracy	✓	✓	✓	✓	✓
Classification accuracy with a point in the HF subrange: 100%. Prediction time 17ms.					

4. CONCLUSION

The method proposed in the paper is based on coupled application of computational intelligence algorithms and expert knowledge. Previously designed microphone classification model has been improved significantly by the implementation of presented method. It is a new approach to the classification of microphones, concerning observation and choice of the working frequency subrange: LF (20-800Hz), flat (800-2000Hz) or HF (2000-20000Hz). Classification is intended to three types of electret microphones, which are commonly used in PA in a whole frequency range, 20Hz to 20 KHz, but it could be easily extended to a sequence of microphones if it is a demand of the experiment.

The method has satisfactory accuracy, with the maximum classification model accuracy of 99.99% in the LF subrange and flat subrange. The model is reliable because it anticipated the microphone type with 100% accuracy in the case of the changed microphone parameters at the given frequency range. It works in real-time mode because once the network was trained, it predicted microphone type in only 17 ms. Even training time of the models for LF and flat subrange fits in the real-time mode. The model met the PA requirements for accuracy, reliability, and real-time work.

The main contribution of this research is the discussion on the minimum required number of measurement points for a precise microphone classification. The domain implied in this research (20Hz to 20KHz) is pretty wide. Using limited frequency range is not a rare PA experimental case. Depending of the chosen domain, practitioner will measure in one, two or three points in order to determine microphone type. This is a huge improvement of the microphone classification procedure and thus the procedure of microphone calibration. Microphone type can be

obtained quickly, reliably, and precisely. The problems of numerous measurement points and slow measurements are solved, too.

Results presented in the paper could be significant for quality control and design of microphones not only for scientific application but for audio techniques and any technique which uses the microphone as a detector.

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