

## Influence of data scaling and normalization on overall neural network performances in photoacoustics



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In our previous articles [1,2] we have shown that the application of artificial neural networks (ANNs) in photoacoustics could improve experimental procedures in many ways: better accuracy and precision in investigated sample parameters prediction, better control of the experimental conditions together with approaching to the real-time characterization of the investigated sample, etc. Here we will try to show why the different types of scaling and normalization procedures could be beneficial to the accuracy, precision and numerical stability of the network predicted parameters and network training speed. To do that numerical (Fig.1) or logarithmic scaling and min-max and max normalizations are applied on experimental input data used in the ANNs training process. At the same time, specific numerical scaling is used for network output data (predicted sample thermal and geometric parameters such as thermal diffusivity, linear coefficient of thermal expansion, thickness) to find possible benefits to ANNs performances. Our analysis of training, stability, and accuracy of network prediction will rely on the ANNs trained with or without scaling and/or normalization to find their influence on overall network performances.

Table 1. Training performance of two neural networks. The first with non-scaled output, the second with normalized output

Type of NN	Performance
non-scaled output	0.059084; 809 epochs ; 4 1/2h
scaled output	0.000037822; 1000 epochs;

Table 2. Maximal and average (%) relative error of two neural networks with differently scaled output layer data.

Type of NN	max (%) relative error			average (%) relative error		
	$D_T$	$\alpha_T$	$l$	$D_T$	$\alpha_T$	$l$
parameters						
non-scaled output	11.8496	7.2159	0.4632	3.9795	1.7724	0.0632
normalized output	0.4824	0.2173	0.4756	0.0661	0.0574	0.0720

Table 3. Maximal and average (%) relative error of two neural networks with differently scaled output layer data in signal prediction of randomly selected parameters in the range of changes of parameters.

Type of NN	max (%) relative error			average (%) relative error		
	$D_T$	$\alpha_T$	$l$	$D_T$	$\alpha_T$	$l$
parameters						
non-scaled output	9.2781	8.0963	3.3938	3.2013	1.8035	0.3448
scaled output	5.7019	6.5365	4.5952	0.5167	0.3886	0.4285

Table 4. Parameter prediction  $D_T$ ,  $\alpha_T$ , and  $l$ , of amplitude neural networks with non-scaled outputs and with normalized outputs on experimental photoacoustic signals. The relative (%) error of prediction of parameters of individual samples is given. Sample no.1 is 830  $\mu\text{m}$ , sample no. 2 is 417  $\mu\text{m}$  and 3 is 128  $\mu\text{m}$ .

Rel error (%)	Sample no.1			Sample no.2			Sample no. 3		
	$D_T$	$\alpha_T$	$l$	$D_T$	$\alpha_T$	$l$	$D_T$	$\alpha_T$	$l$
parameters									
non-scaled output	0.6556	0.3590	0.0133	0.6035	0.9553	0.0831	1.9162	1.6576	2.1096
scaled output	0.0555	0.0421	0.0111	0.1290	0.0263	0.0592	11.7065	5.7570	11.5476

Table 5. Performance of amplitude neural networks with different normalizations.

Type of normalization	Performance, number of epochs
non-normalization	0.000037822
non-normalization on 1	0.00015258 at 240 epoch
logarithmic normalization	0.000045951
max normalization	0.0000041492
min-max normalization	0.00000041263

Table 6. Maximal and average (%) relative error of independent test of extracted amplitudes of photoacoustic signals before training neural networks.

Type of normalization	max relative error %			average relative % error		
	$D_T$	$\alpha_T$	$l$	$D_T$	$\alpha_T$	$l$
parameters						
non-normalization	0.4824	0.2173	0.4757	0.0661	0.0574	0.0720
non-normalization on 1	1.1474	1.0572	1.0963	0.1417	0.1234	0.1700
logarithmic normalization	0.3472	0.2289	0.3882	0.0661	0.0729	0.0679
max normalization	0.1264	0.1998	0.1939	0.0254	0.0352	0.0265
min-max normalization	0.0322	0.0770	0.0605	0.0068	0.0185	0.0084

Fig. 1. Numerically scaled a) amplitudes and b) phases of the photoacoustic signals used as an input data for network training base formation in frequency domain aimed for electronic parameters calculations.

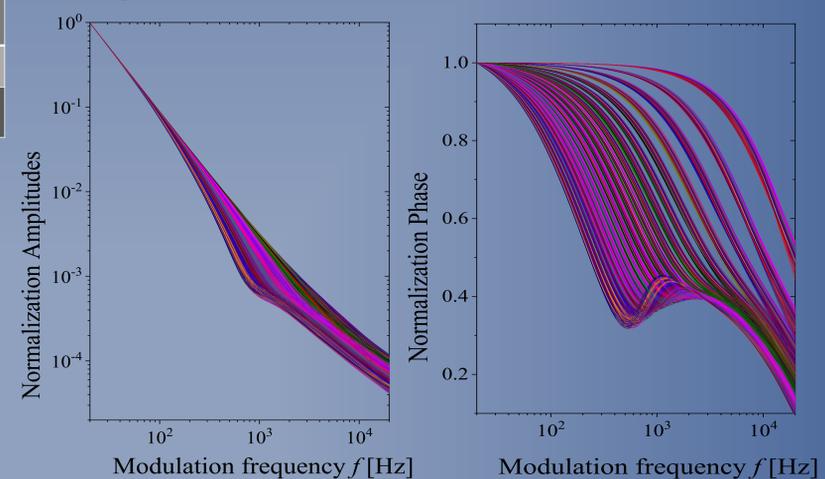


Table 7. Maximum and average (%) relative errors, for parameters thermal diffusivity, expansion and thickness for two groups of amplitudes of photoacoustic signal: (21) amplitudes thickness from 200 to 1000 mm, and (3) amplitudes thickness from 100 to 200 mm.

Type of NN	max (%) relative error			average (%) relative error		
	$D_T$	$\alpha_T$	$l$	$D_T$	$\alpha_T$	$l$
non-normalization 21	0.8021	0.1295	0.6393	0.1177	0.0578	0.0925
non-normalization 3	5.7019	6.5365	4.5952	3.3097	2.7041	2.7805
non-normalization on 1 21	5.1605	1.7776	1.9282	0.5256	0.2269	0.2163
non-normalization on 1 3	69.7347	10.0029	45.8729	26.7540	5.4590	17.6017
logarithmic normalization 21	0.2098	0.5113	0.1928	0.4423	0.3626	0.4781
logarithmic normalization 3	4.3396	5.2192	6.5777	3.1127	2.0302	3.5607
max normalization 21	0.9118	0.3266	1.0072	0.2150	0.1154	0.1787
max normalization 3	3.4993	5.1995	3.4195	1.8928	2.1713	2.3650
min-max normalization 21	0.8201	0.3875	0.6415	0.1650	0.1177	0.1153
min-max normalization 3	2.2324	3.8551	2.4005	1.3770	2.2175	1.7892

Table 8. Relative (%) errors of parameters prediction  $D_T$ ,  $\alpha_T$  and  $l$  of experimental signals by neural networks with different normalized amplitude bases: without normalization, logarithmic normalization, normalization to the maximum value and min-max normalization. Results are shown on three samples: the sample no.1 has 830 mm, sample no.2 has 417 mm and sample no.3 has 128 mm.

Rel. error%	Sample no.1			Sample no.2			Sample no. 3		
	$D_T$	$\alpha_T$	$l$	$D_T$	$\alpha_T$	$l$	$D_T$	$\alpha_T$	$l$
parameters									
no-norm	0.0555	0.0421	0.0111	0.1290	0.0263	0.0592	11.7065	5.7570	11.5476
non-norm on 1	0.0367	0.0812	0.0037	0.1120	0.0635	0.0011	2.8903	2.0515	2.9798
log norm	0.0450	0.0387	0.0204	0.0610	0.0339	0.0130	5.8210	2.3487	6.2749
max norm	0.0672	0.0278	0.0005	0.0774	0.0316	0.0116	1.2337	0.1819	2.3816
min-max norm	0.0366	0.0489	0.0188	0.0651	0.01246	0.0031	2.3220	0.3906	3.1880

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