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Evaluation of Thermophysical Properties of Semiconductors by Photoacoustic Phase Neural Network

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Abstract: The idea of this paper is to develop a method for determination thermal diffusivity, linear expansion coefficient and thickness of a semiconductor sample from photoacoustic phase measurement by using neural network. The neural network has been trained on photoacoustic phases obtained from a theoretical model for semiconductors Si n-type in the range of 20Hz to 20kHz. The accuracy of the prediction of the experimental signal by the phase neural network was analyzed depending on the application of random Gaussian noise to the input base of photoacoustic signals.

Key words: photothermal, photoacoustics, phases, artificial neural networks, optimization, random Gaussian noise, experimental data processing

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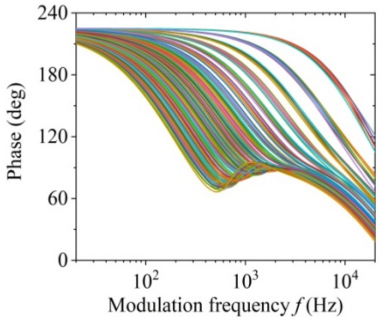
1. Introduction

Photoacoustics is a non-destructive technique that considers the effects of the interaction of light and matter. In the most cases, it is non-contact experimental setup and requires little preparation of samples for the experiment. With the experimental setup of the open photoacoustic cell, the photoacoustic response is recorded with a microphone directly placed on the sample [1-6]. The photoacoustic response (amplitude-phase characteristics) can be used by standard analysis to determine the sample's optical, thermal, elastic and many other properties. Most often, in the analyzes of the results of various photoacoustic settings, only the amplitude characteristics in a narrower frequency range are considered, cutting off the frequency ranges where there is the detection of instrumental influences [7-9].

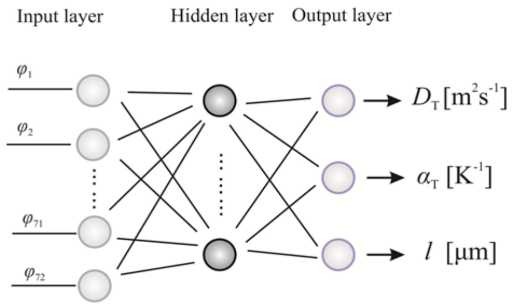
By developing theoretical-simulation models [10-17] of physical effects that exist in a modulated illuminated sample that affects the formation of a signal detected by a microphone, it was possible to develop algorithms for the inverse determination of the parameters of the analyzed sample [18-21]. A neural network algorithm is based on a working replica of the human brain in process of learning from the given data. The structure of neural networks consists of connected neurons that are placed in three layers: input, hidden and output. During training through the neural network, forward and backward, input layer values and output layer values connect. In our case, the phases of photoacoustic signals with the aim of characterizing the sample.The application of neural networks in the inverse solution of the photoacoustic problem showed high precision in determining the parameters from the experimentally recorded signal in the range of 20 to 20kHz. The question arises as to how precisely it is possible to determine parameters from experimentally recorded phases[22], and whether it is possible to apply some optimization method in the application of neural networks.

2. Theoretical background

The sample considered is a circular silicon wafer whose radius is significantly greater than its thickness, which ensures one-dimensional energy transport based on Fourier's law of heat conduction. In the photoacoustics of semiconductors, three effects that lead to the formation of a photoacoustic signal are considered: thermodiffusion, thermoelasticity and plasmaelasticity. The thermodiffusion effect is a consequence of heat conduction through the sample and depends on the thermal diffusivity of the semiconductor sample. The thermoelastic effect is a consequence of mechanical stress caused by photothermally induced temperature gradient within the sample and depends on thermal expansion coefficient and thickness. The plasmaelastic effect is a consequence of the mechanical stress that occurs due to the appearing of concentration gradient of photogenerated carriers. The most influential physical effects create a sound that is experimentally measured and well described by a theoretical simulation model. By changing the parameter in the theoretical simulation model of thermal diffusivity, expansion in the range of 10% from literary values of pure silicon sample and thickness in the range of 100 to 1000 microns, the phase base of >5000 photoacoustic signals is obtained, which is shown in Figure 1a) in degrees (deg) [13-21]. The database was used to train the phase neural network NN0, Figure 1b). In the process of training the NN0 network, an algorithm is activated that connects the data of the input layer, phase φ_1-φ_{72}, with the data of the output layer, thermal diffusivity D_T, thermal expansion α_T and sample thickness l. The number of input neurons 72 is determined by the number of values of the experimentally measured photoacoustic signal. The hidden layer is a single layer, and has 50 neurons. During the time of one epoch, all the data of the input and output databases are used once. By back propagation, correction is made until the minimum error is reached.



a)



b)

Figure 1. a) phase base of photoacoustic signals, b) neural network architecture.

3. Results and discussion

Phase neural network NN0, after training on the basis, Figure 1, achieved exceptional performance of 1.7246×10^{-6} in 1000 epochs, which provides high precision with errors <1% on simulated signals and errors of 30%, 16% and 15% on experimentally recorded signals in the prediction of parameters of thermal diffusivity D_T^{ANN}, expansion α_T^{ANN} and thickness l^{ANN} ..In addition to the neural network NN0, neural networks NN1-5 were also formed by the application random Gaussian noise in degrees % from 1-5 with the aim of adapting the signal base, Figure 1a, to the experimental conditions [5-7].

The basic characteristics of networks NN1-5 are that their training time, which is determined by the number of epochs, decreases (from 44 to 5 epochs) and that their performance decreases (increases from 1.58×10^{-2} to 7.0721×10^{-2}), with increasing % added Gaussian noise (1-5%). In front of the basic characteristics, as a requirement for further use, their precision and time of prediction of parameters of thermal diffusivity, expansion and thickness are imposed. The accuracy of the prediction of these three parameters on the theoretical photoacoustic signals is lost, the errors increase from ~10^{-2} to 11%, while the accuracy in the prediction of the experimental signals becomes better, decreasing to 30%, 16% and 15% at error values <2% in parameter predictions D_T^{ANN}, α_T^{ANN} and l^{ANN}, respectively.

Practical application of formed networks NN0-5 is a test on recorded experimental photoacoustic signals. The results show that the most optimal network for predicting sample parameters from measured photoacoustic signals is a network that has a degree of added random Gaussian noise with a value between 3 and 4%, which fits with the most common measurement uncertainty of photoacoustic phases.

4. Conclusion

The presented results show that it is possible to determine the thermoelastic properties of semiconductors based on the measurement of the phases of the photoacoustic signal when the inverse photoacoustic problem is solved using neural networks. Phase networks without adding noise, although they have a high accuracy on the numerical experiment data, do not show a high accuracy in the real experiment. By adding the Gaussian noise to the base, the networks are trained faster and a much higher accuracy is obtained in determining all sample parameters. Besides, prediction errors show that the optimal adding Gaussian noise is between 3 and 4% corresponding to the uncertainty of the experimental phase measurement.

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