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ANALYSIS OF PRINTED CIRCUIT BOARD LIBS DATA USING DEEP LEARNING

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Abstract. The laser-induced breakdown spectroscopy (LIBS) is a method often used for monitoring the selective removal of thin layers by laser. In this way it is possible to achieve rapid prototyping of printed circuit boards. We show that it is convenient to use deep learning algorithm on LIBS data to obtain an indication that copper layer is fully removed.

1. INTRODUCTION

Rapid prototyping of printed circuit boards can be achieved by laser ablation. One of the possible approaches to this process was presented in Rabasovic et al. 2016. We have used the laser-induced breakdown spectroscopy (LIBS) as a convenient method both for ablation and for monitoring the selective removal of thin layers by laser. In Rabasovic et al. 2016 the LIBS data were analyzed by using correlation coefficients. Nowadays, availability of more and more fast computers, capable of machine learning, moves the analysis algorithms from simple numerical calculation towards the more sophisticated artificial intelligence methods. Our initial efforts for machine learning analysis of LIBS printed circuit board data, using principal component analysis are presented in Sevic et al. 2020. Interesting applications of machine learning algorithms for analysis of LIBS data are presented in Boucher et al. 2015, Moros et al. 2013, Serranoa et al. 2014. State of the art approaches to the problem are reviewed in Porızka et al. 2018, Vrabel et al. 2020; Zhang et al. 2022. In this paper we study the spectral data by using the deep learning algorithm.

2. ARTIFICIAL NEURAL NETWORKS AND DEEP LEARNING

Artificial neural networks (ANNs) mimic the human brain through a set of algorithms. They consist of input layer, hidden layers and output layer. A neural network that consists of more than three layers can be considered a deep learning algorithm, or a deep learning network.

Because of increasing computer efficiency more and more sophisticated machine learning algorithms become extensively used. The data set of certain structure is used to "train" the machine to learn some specific characteristics of input data. Then, machine could be used to recognize and identify these characteristics in newly presented data of similar structure and nature.

3. EXPERIMENTAL SET-UP AND METHODS

Our experimental setup is and its applications for elemental analysis using LIBS, including several ways of processing spectra, are described in detail in Rabasovic et al. 2012, Rabasovic et al. 2014, Rabasovic et al. 2019, Sevic et al. 2011. The data analyzed here were obtained by experimental setup described in Rabasovic et al. 2016; at that time we have calculated the correlation coefficients of measured spectra to identify the moment of achieving the full removal of copper layer by laser ablation. In Sevic et al. 2020 we have implemented the PCA to achieve automatic recognition of the instant when laser ablation of copper layer has been finished and the laser starts damaging the composite substrate of printed circuit board. Here, to achieve the same goal, we use deep learning network. We use Solo + MIA software package (Version 9.0, Eigenvector Research Inc, USA).

4. RESULTS AND DISCUSSION

Plasma breakdown optical spectra of printed circuit board at the start, when only copper is ablated; and when the substrate is fully exposed, are shown in Fig. 1. Their differences could be seen by a naked eye.

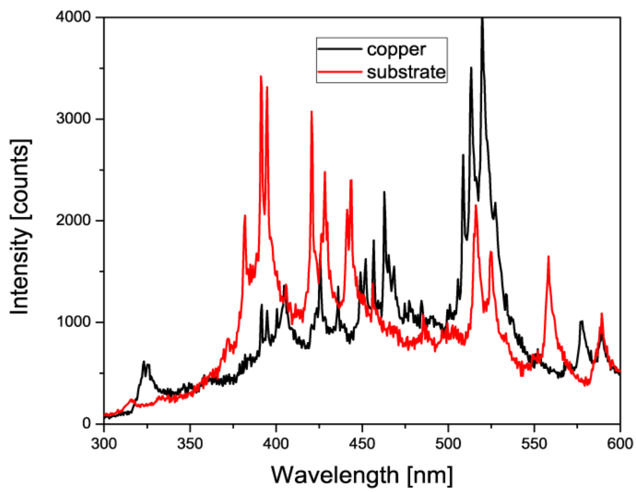

Figure 1: Plasma breakdown optical spectra of printed circuit board at the start, when only copper is ablated; and when the substrate is fully exposed.

At the beggining of the ablation process the peaks observed were neutral Cu lines at 510.55, 515.32, 521.82, and 578.21 nm. The prominent line was Cu I at 521.82 nm.

The presence of characteristic emission lines corresponding to the substrate was an indication to restrict the ablation zone and minimize the damage to the substrate. Any of the prominent lines such as Al I (394.39 nm, 396.19 nm), Ca I (422.64 nm, 616.2 nm), Ca II (393.43, 396. 88 nm), and Na I (589.15 nm) can be used as an indicator of the substrate.

We have trained the deep learning neural network with measured spectra corresponding to ablation of copper layer with 10, 50, 200 and 500 laser shots. We have adopted that output of network should produce the numbers between 1 and 100, corresponding very roughly to percent of laser ablation of copper. If output is higher of, say threshold of 90, then the laser shots should be stopped on that spot and laser beam should be moved further.

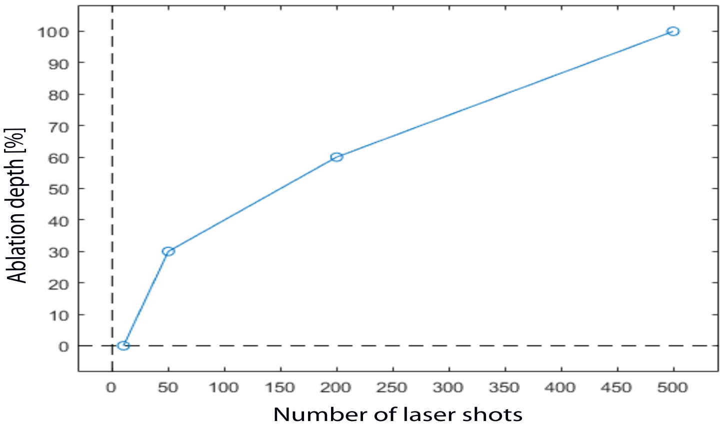

Figure 2: Training of deep neural network.

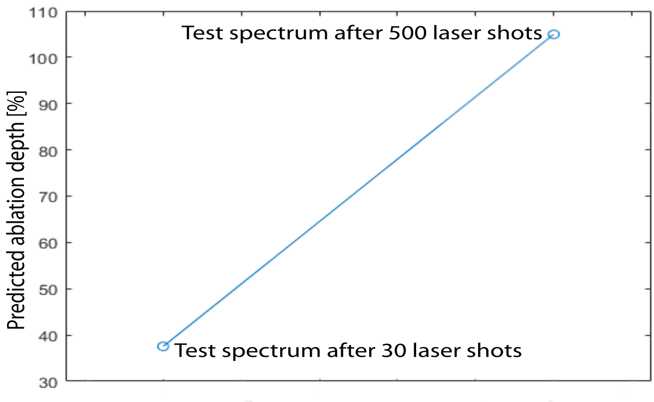

Figure 3: Two tests of trained deep neural network.

We have tested the network with spectra not presented before to the computer; and as expected, the predicted ablation level corresponded roughly to the functional dependence shown in Fig. 2. Two examples are shown in Fig. 3.

5. CONCLUSION

Rapid prototyping of printed circuit boards can be achieved by using laser ablation and LIBS. We have analyzed the LIBS data of printed circuit board by using deep learning algorithm. In our previous analyses we have used the correlation coefficients and PCA to identify the moment when laser ablation reaches the composite substrate of printed circuit board. Now, we have shown that it is possible to automatically detect the instant when the copper layer is fully ablated by deep learning network.

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