Publ. Astron. Obs. Belgrade No. 99 (2020), 117 - 120 *Contributed Paper*

PRINCIPAL COMPONENTS ANALYSIS OF PRINTED CIRCUIT BOARD LIBS DATA

D. SEVIC[1], M. S. RABASOVIC[1], P. GREGORČIČ[2], M. D. RABASOVIC[1] and B. P. MARINKOVIC[1]

[1]*Institute of Physics, University of Belgrade, Pregrevica 118, 11080 Zemun, Serbia*
E–mail sevic@ipb.ac.rs

[2]*Faculty of Mechanical Engineering, University of Ljubljana, Aškerčeva 6, 1000 Ljubljana, Slovenia*

Abstract. One of the ways to achieve rapid prototyping of printed circuit boards is by using the laser ablation. The laser-induced breakdown spectroscopy (LIBS) is a convenient method for monitoring the selective removal of thin layers by laser. In this paper the obtained LIBS data are analyzed by using principal component analysis (PCA).

1. INTRODUCTION

Laser ablation has many applications. Main aim of our research presented in Rabasovic et al. 2016. was rapid prototyping of printed circuit board. 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. 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. In this paper we study the spectral data obtained in Rabasovic et al. 2016. by using the Principal Component Analysis (PCA).

2. PRINCIPAL COMPONENT ANALYSIS

One of the basic machine learning techniques is based on using the principal component analysis. The method is proposed long ago, see Hoteling 1933, Karhunen 1947, Loeve 1948. However, because of their low computing efficiency, the PCA and other, more sophisticated, machine learning algorithms become extensively used only recently.

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.

If X is a data matrix with m rows and n columns, each variable being a column and each sample a row, PCA decomposes X as the sum of r t_i and p_i, where r is the rank of the matrix X:

$$X = t_1 p_1^T + t_2 p_2^T + ... + t_k p_k^T + ... + t_r p_r^T \qquad r \leq \; min\{m, n\} \tag{1}$$

In the PCA decomposition, the p_i vectors are eigenvectors of the covariance matrix; it holds:

$$cov(X) = \lambda_i p_i \tag{2}$$

where λ_i is the eigenvalue associated with the eigenvector p_i.

The t_i, p_i pairs are ordered by the amount of variance captured. The t_i vectors are known as scores and contain information on how the samples relate to each other. The p_i vectors are known as loadings and contain information on how the variables relate to each other. Generally, the PCA model is truncated after k components.

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. Here, we implement 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. We use Solo software package (Version 8.8, Eigenvector Research Inc, USA) for computing the PCA.

4. RESULTS AND DISCUSSION

Streak images of 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.

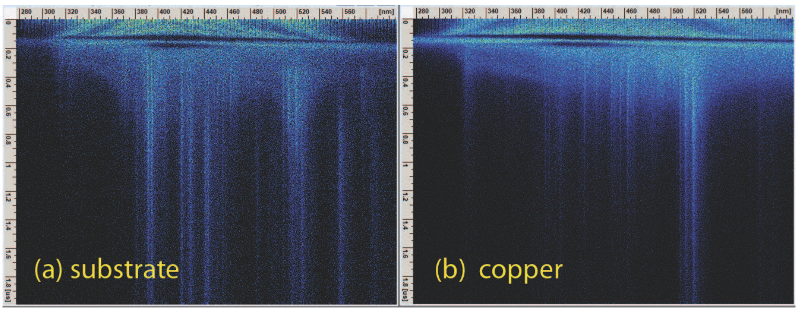

Figure 1: Streak images of plasma breakdown optical spectra of (a) copper conductor and (b) a printed circuit board substrate.

The first two principal components of LIBS data are shown in Figure 2. The plots justify our decision in Rabasovic et al. 2016. to calculate correlation coefficients of spectra in the range between 370 nm and 500 nm. In that range, the principal components look the least noisy.

Scores plot of first two principal components is shown in Fig 3. As expected, the scores corresponding to spectra at start of ablation and at the end of ablation are spaced widely apart, enabling automatic recognition of the moment when the useful ablation ends. The spectra corresponding to partial ablation are somewhere in between on PC1 axis, and widely apart on PC2 axis.

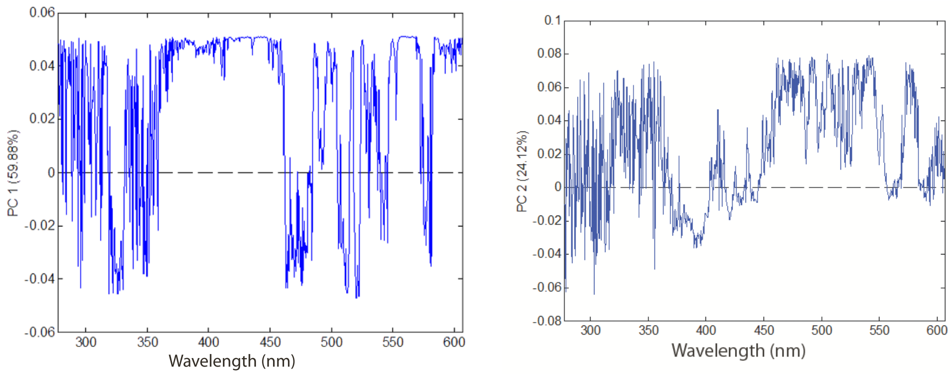

Figure 2: The first two principal components of LIBS data.

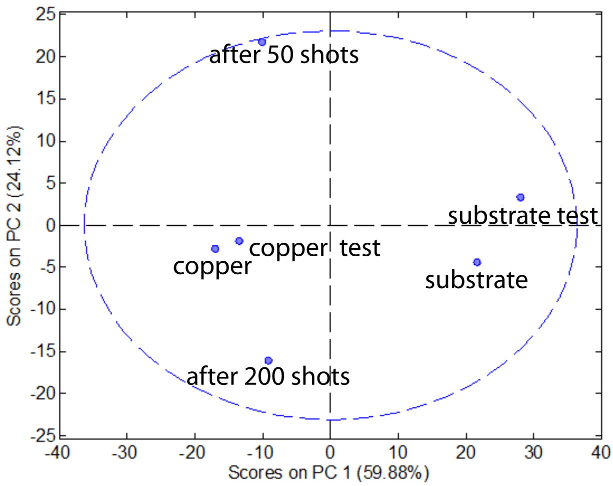

Figure 3: Scores plot of first two principal components.

5. CONCLUSION

The laser ablation is one of the ways to achieve rapid prototyping of printed circuit boards. We have analyzed the LIBS data of printed circuit board by using machine learning algorithm. In our previous analyses we have used the correlation coefficients to identify the moment when laser ablation reaches the composite substrate of printed circuit board. Now, we have proved that it is possible to automatically detect the instant when the copper layer is fully ablated by PCA.

Acknowledgment

This work was financially supported by the Institute of Physics Belgrade, through the grant by the Ministry of Education, Science, and Technological Development of the Republic of Sebia

References

Boucher T.F., Ozanne M.V., Carmosino M.L., Dyar M.D., Mahadevan S., Breves E.A., Lepore K.H., Cleggc S.C. : 2015 *Spectrochimica Acta Part B* **107** 1.

Hoteling, H. : 1933 *Journal of Educational Psychology* **24** 417.

Karhunen, K. : 1947 "ber lineare Methoden in der Wahrscheinlich-keitsrechnung". *Ann. Acad. Sci. Fennicae. Ser. A. I. Math.-Phys.* **37** 1.

Loeve, M. : 1948 *Processus stochastiques et mouvements Browniens, Paris: Gauthier-Villars.*

Moros J., Serrano J., Gallego F.J., Macas J., Laserna J.J : 2013 *Talanta* **110** 108.

Serranoa J., Moros J., Snchez C., Macas J., Laserna J.J : 2014 *Analytica Chimica Acta* **806** 107.

Rabasovic M.S., Sevic D., Pejcev V., Marinkovi B.P. : 2012 *Nucl. Instrum. Meth. B* **279**, 61.

Rabasovic M.S., Marinkovi B.P., Sevic D. : 2014 *IEEE Transactions on Plasma Science* **42**, 2388.

Rabasovic M.S., Sevic D., Lukac N., Jezersek M., Mozina J., Gregorcic P. : 2016 *Appl. Phys. A* **122**, 186.

Rabasovic M.S., Rabasovic M.D., Marinkovic B.P., Sevic D. : 2019 *Atoms* **7**, 6.

Sevic D., Rabasovic M.S., Marinkovic B.P. : 2011 *IEEE Trans. on plasma science* **39**, 2782.