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APPLICATION OF ARTIFICIAL NEURAL NETWORK IN THE ANALYSIS OF THE SPECTRA FROM LASER ABLATION COMBINED WITH FAST PULSE DISCHARGE

NENAD M. SAKAN, MILICA L. VINIĆ, VLADIMIR A. SREĆKOVIĆ, IVAN TRAPARIĆ and MILIVOJE R. IVKOVIĆ

Institute of Physics Belgrade, University if Belgrade, Pregrevica 118, Belgrade, Serbia
E-mail nsakan@ipb.ac.rs

Abstract. The presented work investigates the application of artificial neural networks (ANN) onto spectral classification. The goal of the work was to determine the type of unknown spectra on the basis of a train dataset with the usage of several types of basic ANN. The numerical procedures we are developing, for LIBS analysis of the plasma-facing components of the fusion reactor, was tested on the classification of spectra from different soil or ore types. The data source is a laser ablation combined with fast pulse discharge, the method proposed for the reactor wall analysis. The success in it's application has shown not only that the ANN is usable in case of classification of type of spectra but it presents a step forward making of expert system for the more complex equipment.

1. INTRODUCTION

Classification and determination is a common field for the usage of machine learning. The artificial neural networks (ANN) are most powerful machine learning algorithms (Mishra et. al. 2017). As a test case the simplest shallow and deep neural networks has been selected. As a merit a experimental data from laser ablation assisted plasma source for the cases of clay soil and tile brick are used. The goal was to test if the ANN could achieve precision in determining of the appropriate analyzed material as well as type of plasma as an emitter, and as such to prove the usability of ANN method for the fast classification of the recorded spectra. The test dataset was collected with the advanced, laser ablation combined with fast pulse discharge, enhanced LIBS technique (Vinić et al., 2014).

The main contributions of this research work are as follows:

- We compared the applications of the four ANN of different complexities.
- Utilized the ANN of deep type.

In the flowing section we have described the experimental setup and discussed the results and the future steps.

2. EXPERIMENTAL SETUP

The laser induced breakdown spectroscopy (LIBS) has evolved to a mature technique for the analysis of various samples, from gaseous up to underwater samples. The work has been carried out in order to enhance the emissivity of plasma, the introducing a second pulse, in the case of dual pulse LIBS (DP-LIBS). This technique has made improvement in detection limit and a DP-LIBS is now comparable to other more mature spectroscopy techniques and as such is adopted as a standard spectroscopy technique. The other way of enhancement of the detection limit is fast spark discharge enhanced LIBS, it also has a possibility to excite harder to excite elements such as carbon, chlorine, sulphur and fluorine.

The experimental setup is shown on Figure 1. The investigated material (1.) is irradiated by the 100-mJ nanosecond pulse Molectron model MY-34 Nd-YAG laser (2). The plasma is formed on the sample, as well as inside the fast spark discharge. The radiation is analyzed spectrally as well as temporally with the Andor technology, model Shamrock 303-i spectroscope, coupled with the Andor iStar iCCD camera, model DH 720 -18F-03 (position 3). The time delay for the start of collection a spectral data is determined by the delay unit (4). The electrical behavior of the spark as well as total emissivity is monitored and recorded on the oscilloscope (5). The spark discharge unit consists of capacitor (7), and current probe (8). The photodiode (9) monitores the emissivity of produced plasma.

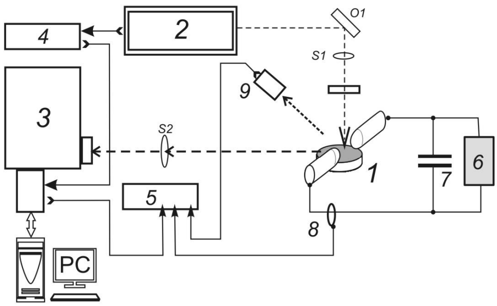

Figure 1: Experimental setup of the system for the laser ablation of the sample material spectroscopy: 1. - investigated material pill, 2. - Nd-YAG laser, 3. - spectroscope with coupled iCCD camera, 4. - delay unit, 5. - oscilloscope, 6. - high voltage supply , 7. - capacitor bank , 8. - current probe.

The set of measurements for clay soil and tile bricks are selected. In the initial time at the delay of 0.1 us, only the LIBS phase of the plasma is visible, in the later recorded spectra, 0.6 us delay, the ablated material is inside spark discharge that was triggered by the LIBS phase plasma. So, the four classes of spectra are recorded and used for ANN training, they are denoted here as clay-LIBS, clay-spark, tile-LIBS and tile-spark. For more details on the technique as well as achieved improvement of the signal to noise ratio please consult (Vinić et al., 2014).

3. ANN THEORY AND TOPOLOGY

The artificial neural network application in various areas of spectroscopy is in growth, from environmental applications up to the analysis of LIBS extraterrestrial probes on Mars rover (Sun et al. 2021). In the literature the LIBS spectroscopy as a tool for determining a lead concentration in soil (Zhao et al. 2019) is coupled with ANN. It is a trend in progress for environmental and geophysical analysis (Tingting et al., 2020). Usually, the package of proven machine learning kit is used, for instance Google kit Keras (https://keras.io/) is often used in LIBS specific applications (Hao et al., 2020), in this work a Keras implementation of feed forward and deep feed forward ANN was made for the investigation of the usability of ANN presented in this manuscript.

4. RESULTS AND DISCUSSION

The prediction was made on the basis of available experimental data set. The selection was made to throw individual CCD lines of data in order to have artificial dataset enlargement with the different areas of plasma observed as well as different noise composition. The random choice of two thirds of the data was used to train the ANN while the one thirds was used to test the prediction.

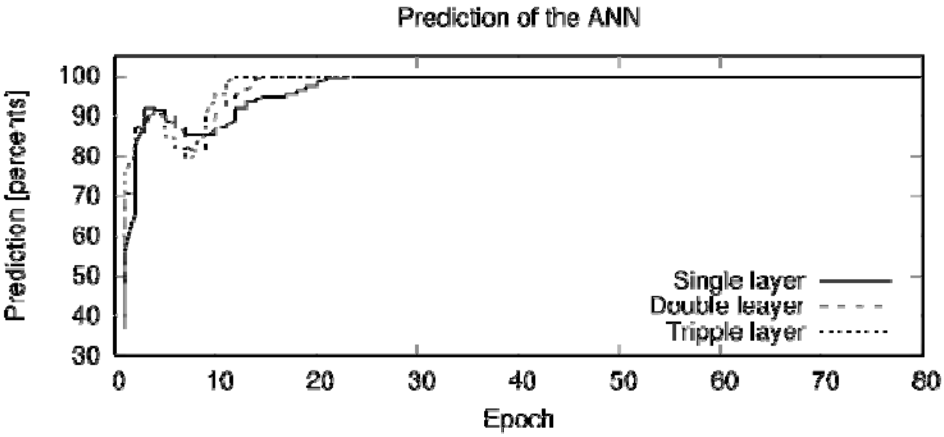

Figure 2: Artificial neural network prediction of the spectra type

The input layer is determined with the dimensionality of input data, so for the available data set the input layer consists of 9927 input neurons. The prediction space consists of four individual outcomes, so the output layer consists of four vectors: [1 0 0 0] – clay-LIBS; [0 1 0 0] – clay-spark; [0 0 1 0] – tile-LIBS; and [0 0 0 1] – tile-spark. The output layer of ANN consists of four neurons belonging to each output vector. Three networks were compared, simplest one consists of only one hidden layer of 15000 neurons, the two layers one with additional 512 neuron second hidden layer, and third one, most complex, consisting of three hidden dense layers of 15000, 1200 and 256 neurons consequently. The output of four consecutive runs was recorded for each of the three investigated ANN. The output outcome was shown on Figure 2. The most complex ANN consist of three hidden dense layers is the one that converged fastest towards the 100% prediction. It could be seen that the process of selection of investigated spectra could be conducted with the help of ANN.

5. CONCLUSIONS AND PERSPECTIVES

From the presented results it is possible to make several conclusions, as first it could be seen that the determination of target type as well as plasma condition, as an emitter could be achieved with ANN successfully. The further conclusion is made by the analysis of the convergence, the more complex, deep ANN, could be more usable for investigation of the further applicability of the method. More over, the third one, is that the sensitivity on the type of emitter, the type of plasma with the ablated material, could lead to more advanced application of inverse methods, to enable prediction of the emitted spectra based on input variables as laser energy, buffer gas, pressure, composition of target and so on.

The paths for the further development, enlarging the data base of the training sets in order of making a more precise determination of the investigated spectra category, the outcome could be enlarged sensitivity on both target material composition as well as plasma conditions. In the case of large training set the interpolation of the known cases is more precise so the inverse problem could be tested. The other result could be more sensitive selection between the spectra that could not be easily dissolved by human eye or the in depth analysis of data could be both time and effort consuming process. Finally, a set of trained ANN could be generated for the in field usage for the specific tasks, e.g. the path towards the production of expert systems.

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