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Analysis of laser induced plasma plume in atmosphere using deep learning

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Abstract. The regression analysis of spectra of laser initiated electric discharge spark in atmosphere is presented here. Spectral images of optical emission of atmospheric plasma are obtained by a streak camera and integrated in time to obtain sample spectra of plasma with different apparent temperatures. We already have analyzed such spectra using principal component analysis and classification techniques. Now, we have advanced research through the ANN and deep learning technique. Namely, large set of measured spectra are used to train the artificial neural network to obtain the estimation of apparent plasma temperature. For machine learning approach to data analysis we use Solo+Mia software package (Version 9.0, Eigenvector Research Inc, USA).

Key words: Machine learning – Deep learning – Laser induced breakdown spectroscopy

1. Introduction

Various machine learning (ML) techniques are used more and more for analysis of LIBS data. The combination of the popular machine learning algorithms (PCA and LDA, unsupervised and supervised techniques, respectively) with LIBS are used to complete rapid and precise classification of different samples Bellou et al. (2020); Diaz et al. (2020); Pořízka et al. (2018); Yang et al. (2020); Zhang et al. (2022). An artificial neural network (ANN) algorithm is also used for the determination of electron temperature and electron number density in LIBS Borges et al. (2014); D'Andrea et al. (2015) The advantage of ANNs is in the possibility of reproducing nonlinear relations between the inputs and the output(s).

In our recent work we have combined several machine learning techniques, such as K-nearest neighbors classification together with clustering algorithms in supervised manner which is possible in SOLO software, in order to estimate apparent plasma temperature Rabasovic et al. (2022). In that study we have analyzed the possibilities of using ML for analysis of optical spectra emitted by laser induced breakdown and electric discharge spark in atmosphere.

Now, we have advanced research through the ANN and deep learning technique. Namely, set of measured spectra, of copper plasma in air, similarly obtained as in Rabasovic et al. (2022), are used to train the artificial neural network to achieve the estimation of apparent plasma temperature. For machine learning approach to data analysis we use Solo+Mia software package (Version 9.0, Eigenvector Research Inc, USA) Wise et al. (2006).

2. Methods

Our experimental set-up for obtaining the training spectra for deep learning ANN (ANNDL) is explained in detail in Rabasovic et al. (2022). Shortly, spectral images of optical emission of atmospheric plasma are obtained by a streak camera and integrated in time to obtain sample spectra of plasma with different temperatures. It should be pointed out that, because streak images are resolved in time, we were capable to select time windows for integrating spectra in such a way that intensive optical emission of initial plasma was not included.The apparent electron temperature was calculated using the well known Boltzman plot technique, assuming a local thermal equilibrium (LTE) and also that the plasma is optically thin (absorption and scattering can be neglected) Asamoah & Hongbing (2017); Shaikh et al. (2006). The measured copper atomic lines at wavelength of 510, 515 and 522 nm were used to calculate the electron temperature.

For training the ANNDL we have used the set of 55 copper spectra for input vectors. As output vector we have used the set of calculated apparent electron temperatures of plasma, corresponding to those 55 input vectors.

3. Results and discussion

Measured (calculated by Boltzman plot) temperatures of training set are shown in Fig. 1. Plot of predicted temperatures looks much the same, so we omit to present it here.

The general idea of estimating the electron temperature using ANNDL is to train the network using sample spectra for which the temperature is calculated using Boltzman plot. Through training phase the network iteratively minimizes errors between the calculated and predicted temperatures.

Residuals (differences) between the calculated (used for training) and predicted temperatures obtained by deep learning neural network model are shown in Fig. 2. Errors for the samples inside the training set are relatively small, about 1.25 % is the largest one.

After feeding the network with samples with known, calculated temperatures, and if we were satisfied that residuals are acceptably small, the network could be fed by spectra not seen before.

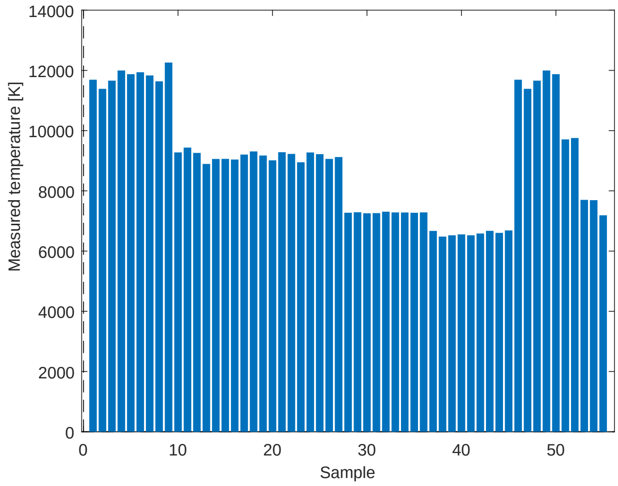

Figure 1. Measured (calculated by Boltzman plot) temperatures of training set.

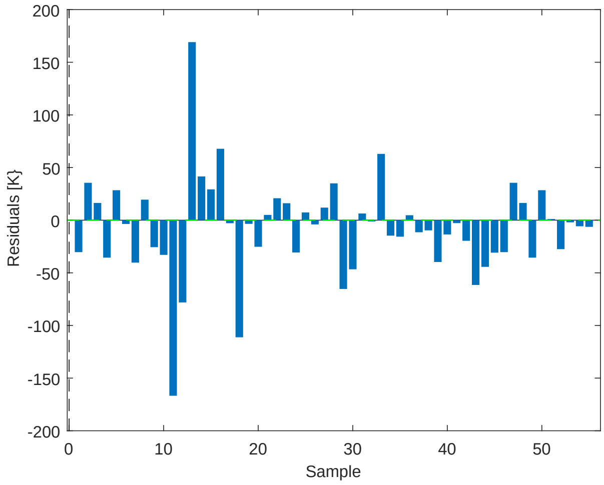

Figure 2. Residuals (differences) between the calculated (used for training) and predicted temperatures obtained by deep learning neural network model.

Table 1. Calculated (using Boltzman plot) and by deep learning neural network predicted temperatures of test samples and their differences.

	Temperature [K]		
Test sample	Calculated	Predicted	Difference
1	11595	11748	-152
2	9400	9221	178
3	8609	9014	-405
4	7331	7283	49
5	6631	6610	21

Fig. 3 shows the predicted temperatures of 5 test samples. Table 1 shows calculated (using Boltzman plot) and by deep learning neural network predicted temperatures of test samples and their differences.

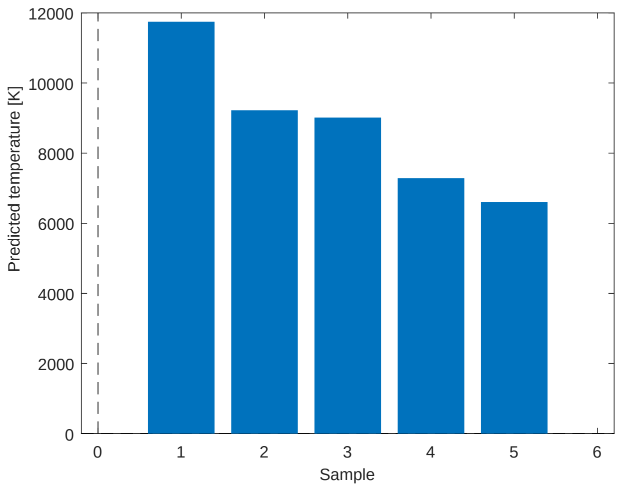

Figure 3. Predicted temperatures of 5 test samples.

Systematic errors when using Boltzman plot come mainly from the uncertainties in the transition probabilities and the measurement of the intensity of spectral lines Shaikh et al. (2006), where uncertainties are estimated to be at least 10 %, so estimation errors visible in Table 1 look fully acceptable. The largest error is about 4.7 %.

4. Conclusions and Discussion

We have used deep learning ANN to estimate the electron temperature of plasma. We have proved that, instead of using the usual way of identifying the spectral peaks and calculating their intensity ratio, it is possible to train the computer by feeding the ANNDL by known spectra with calculated temperatures to estimate the temperature of the spectra not seen before.

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