

Determination of composition of mixed biological samples using laser-induced fluorescence and combined classification/regression models

Lea Fellner¹, Marian Kraus¹, Arne Walter¹, Frank Duschek¹, Thomas Bocklitz^{2,3}, Valentina Gabbarini⁴, Riccardo Rossi⁴, Alessandro Puleio⁴, Andrea Malizia⁴, and Pasquale Gaudio⁴

¹ DLR Institute of Technical Physics, Im Langen Grund 1, 74239 Hardthausen, Germany

² Institute of Physical Chemistry, Friedrich Schiller University Jena, Helmholtzweg 4, 07743 Jena, Germany

³ Leibniz Institute of Photonic Technology, Albert-Einstein-Str. 9, 07745 Jena, Germany

⁴ Department of Industrial Engineering, University of Rome Tor Vergata, Via del Politecnico 1, 00133 Rome, Italy

Received: 2021/04/12 / Revised version: date

Abstract. Laser-induced fluorescence (LIF) provides the ability to distinguish organic materials by a fast and distant in situ analysis. When detecting the substances directly in the environment, e.g. in an aerosol cloud or on surfaces, additional fluorescence signals of other fluorophores occurring in the surrounding are expected to mix with the desired signal. We approached this problem with a simplified experimental design for an evaluation of classification algorithms. An upcoming question for enhanced identification capabilities is the case of mixed samples providing different signals from different fluorophores. For this work, mixtures of up to four common fluorophores (NADH, FAD, tryptophan, and tyrosine) were measured by a dual wavelength setup and spectrally analyzed. Classification and regression are conducted with neural networks and show an excellent performance in predicting the ratios of the selected ingredients.

1 Introduction

Environmental monitoring of biological agents is a key issue in the safety and security fields. It aims at avoiding the natural, accidental and intentional spreads of hazardous agents, with dangerous or even lethal consequences for the local community. Nowadays, the environmental biomonitoring is frequently performed by sampling and successive laboratory analyses, which make the monitoring discontinued, sporadic and usually ineffective (especially time-consuming). Living organisms ubiquitously contain numerous fluorophores such as coenzymes and amino acids that tend to fluoresce when excited by electromagnetic radiation of a certain wavelength [1, 2]. Hence, agents of different fluorophore compositions emit different fluorescent spectra. This property makes laser-induced fluorescence (LIF) spectroscopy a valid technique for the detection and classification of biological agents like pathogenic bacteria, allowing developing a specific instrument for the continuous biomonitoring by standoff detection. Since not all fluorescent matter is dangerous, a proper classification of the agents must be achieved by a spectroscopic approach, in order to distinguish between dangerous and safe cases.

When detecting biological threats without prior sample preparation, fluorescence from other organic material occurring in the environment is expected. Although the classification of pure samples of bacteria [3] and viruses [4] is highly performant, algorithms able to classify the presence of different classes in a mixed sample have not been deeply investigated. The capability to discriminate agents in mixtures or in the environment with fluorescent background is fundamental to develop an instrument which works under realistic conditions, avoids false alarms and guarantees a high sensitivity [5]. Because biological agents frequently have similar spectra, their discrimination may be challenging, even in pure samples [1–3, 6, 7]. In mixed samples, the measured spectrum is a combination of the emission of all fluorescent matter and possible interactions (e. g. quenching), making the discrimination of single classes even more challenging. In the last decades, machine learning approaches have become powerful tools for problems and are the state-of-the-art technology to analyze complex systems with large quantities of data. For LIF spectroscopy, machine learning algorithms, such as neural networks and decision trees, have been successfully applied to the classification of pure biological agents. High classification performances (more than 90%) have been obtained in the most of applications, remote sensing included. On the contrary, no results and detailed investigations about the concentration measurements and classification of mixture samples are available in the literature [4, 8–10].

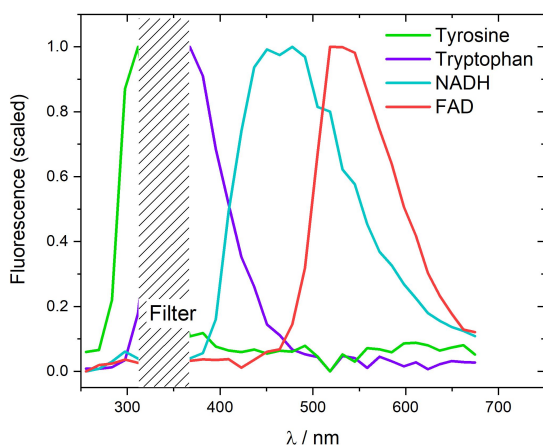


Fig. 1. Scaled fluorescence spectra of Tyrosine (green), Tryptophan (purple), NADH (turquoise), and FAD (red) after excitation with 266 nm.

The present work is a resumption of a previous article [11] where probes of different bacteria could be distinguished by using their LIF signals. In this context, two of the most frequently asked questions address the ambiguity in handling either mixed samples or substances on unknown surfaces. A solution of the latter one has already been applied for a patent [12]. And here, seizing the first question, the classification and prediction of concentrations of different agents in mixed samples is investigated with LIF data. The algorithm for mixture classification is based on a neural network (NN) approach [13–19]. The algorithm is tested with four bio-fluorophores in different ratios and concentrations: nicotinamide adenine dinucleotide (NADH), flavin adenine dinucleotide (FAD), tyrosine (TYR), and tryptophan (TRP). To avoid metabolic variations of living biological samples, these defined substances have been chosen for this first investigation. To the authors’ knowledge, the results have validated for the first time the applicability of LIF to classify and predict the relative concentration of each agent contained in a mixed sample.

2 Materials and methods

Fluorescence spectra were recorded with a dual-wavelength setup described by Gebert et al.[11], providing with alternating pulses of a Nd:YAG laser at 266 nm and 355 nm with a repetition rate of 100 Hz and pulse lengths of 0.7 ns. Pulse energies are adjusted for each sample up to 250 μJ depending on the fluorescence intensity. A Newtonian telescope with diameter of 400 mm is used to collect the fluorescence emission from 22 m standoff distance. The signal is guided to a spectrometer with 32 channels covering the optical range from 250 nm to 680 nm. Each record includes 100 times the spectral response for both excitation wavelengths. All measurements (see Fig. 1) were performed starting with stock solutions of TYR, TRP, NADH, and FAD. These have been diluted and mixed to 159 different samples and between 100 and 800 fluorescence spectra have been recorded.

From the acquired data, channels with misleading information (e.g. spectral regions which are below excitation or blocked by optical filters) are discarded. For both excitation wavelengths, spectra are scaled from 0 to 1 for a comparative usage and as a necessary for later data processing. The overall data set consists of 88100 spectra containing information of 43 fluorescence features.

The algorithm developed in this work consists of an ensemble of feed forward neural networks. Being the algorithm supervised, the spectra have been divided into primary training set and "primary" test set. The primary training set is the effective training set of the ensemble. For each neural network it is randomly divided into "secondary" training set, validation set and test set (Fig. 2). Each neural network solves a regression problem and is trained to predict the relative concentration of each agent. Then, the mean and the standard deviation of each relative concentration is calculated using the output of each neural network. The mean concentration is the concentration predicted by the algorithm and the standard deviation is its uncertainty. The presence of one agent (classification problem) is then calculated by a hypothesis test (t-test), where the null hypothesis is that there is not the agent. Thus, the t-score is calculated as the mean concentration divided by its standard deviation. If the t-score is higher than a specific threshold (which is optimized according to the acceptable type-1 error), the algorithm rejects the null hypothesis and classifies the agent as "present". Then, the ensemble is applied to the primary test set (which has never been included for training the model) as required.

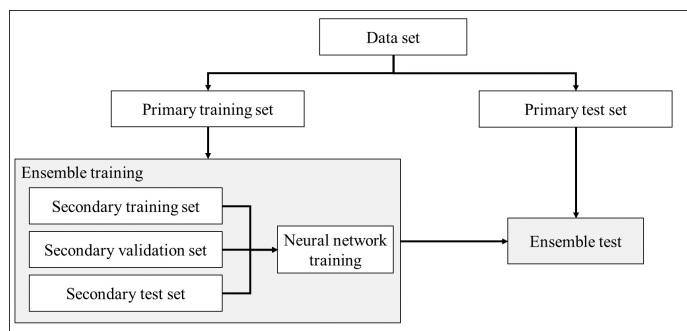


Fig. 2. Schematic illustration of the developed algorithm. After splitting the data into two primary sets, the final prediction models are tested only with the test set excluded.

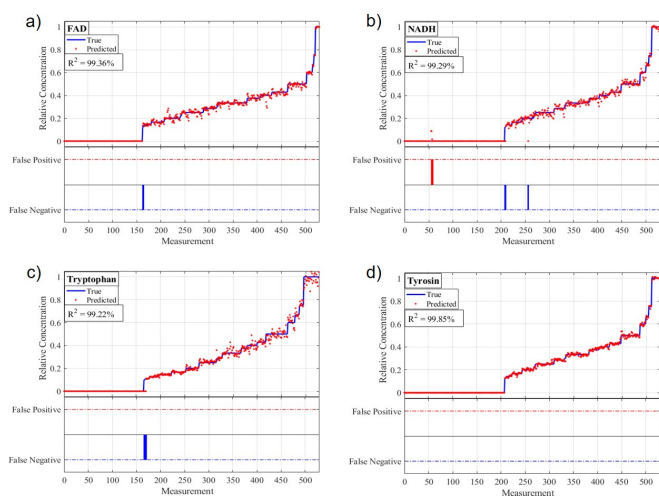


Fig. 3. Relative concentration as function of the measurements. FAD (a), NADH (b), TRP (c), and TYR (d) sorted in ascending concentration (blue line: actual value, red dots: predicted value). The lower panels highlight false negative or false positive predictions for each substance).

Table 1. Fit results for regression model (R^2), and sensitivity and specificity of the classification model

Substance	R^2	Sensitivity	Specificity
FAD	0.994	0.995	1.000
NADH	0.993	0.991	0.986
TRP	0.992	0.986	1.000
TYR	0.998	1.000	1.000

3 Results

Fig. 3 shows the combined results after classification and regression of the test data set. The scatter plots in the top panels of each subfigure show for each substance the relative concentration as function of the measurements sorted in ascending concentration. The bar plots (bottom) show the false positives (red) and the false negatives (blue). The generated models are applied to the primary test set. The grids show the combined results after classification and regression. The measurement indices are sorted according to the true ratios. Blue lines represent the actual, the red dots are the predicted values. For each substance the coefficient of determination R^2 is found to be larger than 0.99. The bar plots (bottom) show the false positives in red and the false negatives in blue. The goodness of the regression fit and the classification performance given by sensitivity and specificity is given in Tab. 1. The average goodness of the regression fit is given by the coefficient of determination R^2 and found to be higher than 99.4 %, and the calculated classification performances in terms of sensitivity and specificity is 99.3 % and 99.65 %, respectively.

4 Summary

In this evaluation, substances have been selected with clearly different fluorescence signatures (Fig. 1). It is to be expected, that a discrimination of samples with higher similarity in their fluorescence features, will become more challenging. However, the approach in this work, combining classification and regression, demonstrates the ability to predict the presence of an agent in a mixture of substances and to predict ratios of mixed fluorophores by LIF. These findings are of high importance in the development of an instrument for biological detection. For that, one may distinguish firstly between hazardous and non-hazardous agents. Moreover, the disturbing influence of background materials may be strongly decreased. Since it is expected that the classification performances of one agent will strongly drop if its fluorescence intensity is in the order of the background signal, a sensitivity analysis is recommended regarding the maximum of the fluorescence signal ratios. Detailed analyses and discussions about performance, potential and limitation are still in progress and will be fully presented in a future work.

5 Declarations

5.1 Funding

Not applicable

5.2 Conflicts of interest/Competing interests

Not applicable

5.3 Availability of data and material

Not applicable?

5.4 Code availability

Not applicable?

5.5 Authors' contributions

Lea Fellner: Conception, Experimental, Draft, Revision; Marian Kraus: Conception, Data Analysis, Draft, Revision; Arne Walter: Conception, Experimental, Draft, Revision; Frank Duschek, Conception, Revision, Supervision; Thomas Bocklitz Revision, Supervision; Valentina Gabbarini: Conception, Experimental, Draft; Riccardo Rossi: Conception, Data Analysis, Draft; Alessandro Puleio: Conception, Analysis, Draft; Andrea Malizia: Revision, Supervision; Pasquale Gaudio: Draft, Revision, Supervision

References

1. Joseph R. Lakowicz. *Principles of Fluorescence Spectroscopy*. Springer, third edition edition, 2006.
2. Steven C. Hill, Yong-Le Pan, Chatt Williamson, Joshua L. Santarpia, and Hanna H. Hill. Fluorescence of bioaerosols: mathematical model including primary fluorescing and absorbing molecules in bacteria: errata. *Optics Express*, 22:22817–22819, 2014.
3. Frank Duschek, Lea Fellner, Florian Gebert, Karin Grünewald, Anja Köhntopp, Marian Kraus, Peter Mahnke, Carsten Pargmann, Herbert Tomaso, and Arne Walter. Standoff detection and classification of bacteria by multispectral laser-induced fluorescence. *Adv. Opt. Techn.*, 6(2), 2017.
4. Valentina Gabbarini, Riccardo Rossi, Jean-François Ciparisse, Andrea Malizia, Andrea Divizia, Patrizia De Filippis, Maurizio Anselmi, Mariachiara Carestia, Leonardo Palombi, Maurizio Divizia, and Pasqualino Gaudio. Laser-induced fluorescence (LIF) as a smart method for fast environmental virological analyses: validation on picornaviruses. *Scientific Reports*, 9(1), aug 2019.
5. Charles A. Primmerman. Detection of biological agents. *LINCOLN LABORATORY JOURNAL*, 12(1):1–32, July 2000.
6. Research and Technology Organisation. Laser based stand-off detection of biological agents (détection à distance des agents biologiques à l ' aide du laser). Technical report, NATO, 2010.

7. Yong-Le Pan. Detection and characterization of biological and other organic-carbon aerosol particles in atmosphere using fluorescence. *Journal of Quantitative Spectroscopy and Radiative Transfer*, 150:12–35, 2015. Topical issue on optical particle characterization and remote sensing of the atmosphere: Part I.
8. Andrea Malizia and Marco D'Arienzo, editors. *Comparison of classification methods for spectral data of laser induced fluorescence*. Springer-Verlag GmbH, 2018.
9. Simon Ruske, David O. Topping, Virginia E. Foot, Paul H. Kaye, Warren R. Stanley, Ian Crawford, Andrew P. Morse, and Martin W. Gallagher. Evaluation of machine learning algorithms for classification of primary biological aerosol using a new UV-LIF spectrometer. *Atmospheric Measurement Techniques*, 10(2):695–708, mar 2017.
10. Lea Fellner, Marian Kraus, Florian Gebert, Arne Walter, and Frank Duschek. Multispectral LIF-based standoff detection system for the classification of CBE hazards by spectral and temporal features. *Sensors*, 20(9):2524, apr 2020.
11. Florian Gebert, Marian Kraus, Lea Fellner, Arne Walter, Carsten Pargmann, Karin Grünewald, and Frank Duschek. Novel standoff detection system for the classification of chemical and biological hazardous substances combining temporal and spectral laser-induced fluorescence techniques. *The European Physical Journal Plus*, 133(7):269, July 2018.
12. Arne Walter, Marian Kraus, Frank Duschek, and Jonas Grzesiak. Verfahren zum identifizieren einer substanz an einer oberfläche, 2020.
13. William G. Baxt. Use of an artificial neural network for data analysis in clinical decision-making - the diagnosis of acute coronary occlusion.pdf. *Neural Computation*, 2(4):480–489, dec 1990.
14. S. Knerr, L. Personnaz, and G. Dreyfus. Handwritten digit recognition by neural networks with single-layer training. *IEEE Transactions on Neural Networks*, 3(6):962–968, 1992.
15. Harry B. Burke. Artificial neural networks for cancer research: Outcome prediction. *Seminars in Surgical Oncology*, 10(1):73–79, jan 1994.
16. Venkat Subramanian, Ming S. Hung, and Michael Y. Hu. An experimental evaluation of neural networks for classification. *Computers & Operations Research*, 20(7):769 – 782, 1993.
17. G.P. Zhang. Neural networks for classification: a survey. *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, 30(4):451–462, 2000.
18. Dar-Shyang Lee, Sargur N. Srihari, and Roger Gaborski. Bayesian and neural network pattern recognition: a theoretical connection and empirical results with handwritten characters. In *Artificial Neural Networks and Statistical Pattern Recognition - Old and New Connections*, pages 89–108. Elsevier, 1991.
19. Harry B. Burke, Philip H. Goodman, David B. Rosen, Donald E. Henson, John N. Weinstein, Frank E. Harrell Jr., Jeffrey R. Marks, David P. Winchester, and David G. Bostwick. Artificial neural networks improve the accuracy of cancer survival prediction. *Cancer*, 79(4):857–862, 1997.