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Identification of plastics in foodstuff using Rapid-FLIM and neural networks

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Summary: The analysis of fluorescence lifetimes has the potential to reliably differentiate plastics from foodstuffs. A setup for use in an industrial process is required to work in real time. The combination of Rapid fluorescence lifetime imaging microscopy (Rapid-FLIM) and neural networks shows significant improvements in capture time compared to other FLIM technologies, while achieving a reliable differentiation of foodstuffs and plastics.

Keywords: food safety, Rapid-FLIM, FD-FLIM, neural networks, MLP

Introduction

Plastics, due to their light weight and additional useful properties, are widely used in food packaging, both for the packaging itself and parts of machines in industrial food production. This prevalence leads to an issue of contamination with these ubiquitous materials through errors or wear of machine parts. Currently used detection processes struggle to differentiate organic materials like plastics from the inherently organic food stuffs processed.
The use of fluorescence lifetime for the detection of polymers in foodstuffs has been shown to be feasible [1]. This work aims to explore the potential of a frequency-domain based technology, focused on a faster measurement procedure while retaining the promising results of frequency-domain fluorescence lifetime imaging microscopy (FD-FLIM) [2].

State of the art

Fluorescence lifetime

Fluorescence describes the emission of a photon by a molecule or atom after absorption of a photon of shorter wavelength. Fluorescence lifetime, a material specific measure, is defined as the time between peak fluorescence intensity and $\frac{1}{e}(\approx 37\%)$ intensity [3].

FD-FLIM and Rapid-FLIM

The approach of FD-FLIM and Rapid-FLIM relies on the mathematical features of emission signals in the frequency domain.
The sample is excited by a modulated laser. For FD-FLIM, $n = 16$ images are captured, using a special pco.flim camera. Every image contains a Tap A and B, both capture half a period of the signal. The trigger switching Tap A and B is shifted by $\frac{1}{n} * 2\pi$ for every image relative to the laser modulation signal to allow a reconstruction of the emitted signal.

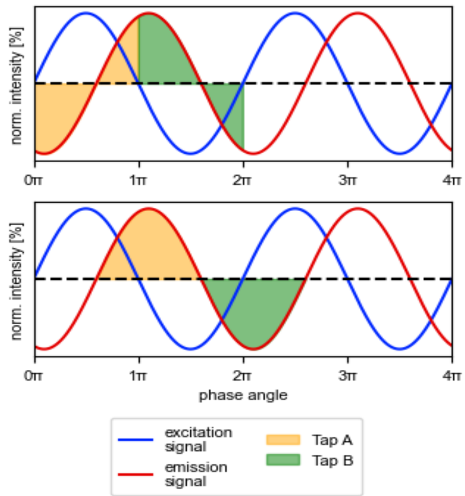

Fig. 1: Imaging process of Rapid-FLIM

From the phase-shift and amplitude dampening relative to the modulation signal, two distinct lifetimes are calculated. In contrast, Rapid-FLIM relies on two images, therefore reducing the capture time by a factor of eight. To gather the greatest amount of information within two images, the trigger-shift of the second image is set to maximize the intensity difference between the images, an example is shown in Fig. 1. Instead of a lifetime, an alternative measure, the normalized intensity difference, shown in equation (1), is calculated describing the normalized difference in the intensity of Taps A to the intensity of Taps B in a range from -1 to 1. A visualization as an image can be found in Fig. 2.

$$X_R = \frac{I_A - I_B}{I_A + I_B} \tag{1}$$

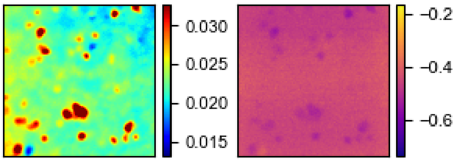

Fig. 2: normalized intensity and intensity difference of S015_M03_RF080

Tab. 1: Sample Overview

Sample	Product	Type
S001	Salami	food
S002	Ham	food
S004	Cheese	food
S005	Gouda	food
S006	Flour	food
S007	Sugar	food
S008	Oat flakes	food
S009	Ham fat	food
S014	Rubber gloves	plastic
S015	Conveyor belt front	plastic
S020	Conveyor belt back	plastic
S024	Yellow sausage	food

Sample Preparation and Data

The used dataset consists of 2362 measurements of twelve samples, ranging from processed foodstuffs, bought at a local supermarket, e.g., cheese and salami, to rubber gloves and conveyor belts. A complete overview of the samples including labels is given in Tab. 1.
Measurements are taken under a microscope, using a pco.flim FLIM-camera with a in house developed python-program and a $445\ nm$ laser as light-source. Measurements are saved as .npy files with sample name, measurement number and trigger phase-shift documented in the filename, e.g., "S001_M099_RF080.npy".

Multilayer Perceptron

In the first run, the model is trained on 100 images of each sample, using k-fold cross validation (k=5) to increase the utilization of the dataset. Using a detailed confusion matrix, incorporating the differentiation of different food types as well, the developed MLP reaches a weighted F1-score of $77\ \%$. Shrinking this matrix to a binary classification of foods and plastics yields an F1-score of $82\ \%$. In the detailed confusion matrix, it can be seen, that three samples in particular are difficult to differentiate from plastics: S002, S005 and S0024, the individual F1-scores are shown in Tab. 2 in column 'all'. For the following development, metrics are focused on those samples.

Tab. 2: Improvement of classification by measures

	all	data	features	filter
S002	$60.4\ \%$	$77.0\ \%$	$91.5\ \%$	$96.0\ \%$
S005	$85.7\ \%$	$95.0\ \%$	$95.8\ \%$	$97.8\ \%$
S024	$77.8\ \%$	$88.8\ \%$	$98.4\ \%$	$97.1\ \%$

The next version is focused on binary classification of the identified difficult food samples against plastics with a larger dataset consisting of 400 images for each food sample and 200 images for each plastic sample. The additional data improves the performance significantly, see Tab. 2 in column 'data'.
To further boost the performance, additional statistical features of the images, namely the range, variance, and inter-quartile range (IQR) are implemented with good results, see Tab. 2 in column 'features'.
Additionally, a change in the measurement setup, the change from a $460\ nm$ long pass filter to a $490/60\ nm$ bandpass filter increased the performance to the overall best results, see Tab. 2 in column 'filter'.

Results and Conclusion

The results prove the feasibility of Rapid-FLIM to differentiate plastics from specific food samples. This training on a binary classification between one food sample and a range of plastics is close to a use case in industrial food processing, where process lines mostly are specialized for one type of food stuff.
The reduction of capture time by a factor of eight vastly improves on one of the flaws of FD-FLIM in real-time scenarios.

Acknowledgement

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References

[1] M. Versen, M. Wohlschläger, H. Langhals, and C. Laforsch, "The detection of organic polymers as contaminants in foodstuffs by means of the fluorescence decay of their auto fluorescence," *Food and Humanity*, vol. 3, p. 100 363, 2024, ISSN: 29498244. DOI: 10.1016/j.foohum.2024.100363.

[2] S. Heitzmann, M. Wohlschläger, N. Leiter, M. Löder, M. Versen, and C. Laforsch, "Classification of foods and plastics using fd-flim and neural networks," in *2024 IEEE Sensors Applications Symposium 2024*, pp. 1–6.

[3] J. R. Lakowicz, *Principles of Fluorescence Spectroscopy*. New York (USA): Springer Science+Business Media, 2006, ISBN: 978-0 387-31278-1.