Towards non-contact pollution monitoring in sewers with hyperspectral imaging

P. Lechevallier[1,2*], C. Felsheim [3], J. Rieckermann [2]

[1] *ETH Zürich, Institute of Environmental Engineering, 8093 Zürich, Switzerland*

[2] *Eawag, Swiss Federal Institute of Aquatic Science and Technology, 8600 Dübendorf, Switzerland*

3 Headwall Photonics, Bolton, USA

** Corresponding author email: pierre.lechevallier@eawag.ch*

Highlights

- First reported use of hyperspectral imaging to measure wastewater pollution
- A combination of pixel classification and data-driven regression is used for pollution measurement
- The model prediction for turbidity: R^2 =0.967, and for COD: R^2 =0.795

Extended abstract

Hyperspectral imaging is a good candidate to face the challenges of sewer pollution monitoring

Pollution from urban drainage systems (UDS) are relevant, but largely unknown (Pistocchi 2020). This is, among other things because reliable online sensors are missing. Nowadays, the monitoring of UDS pollution is done either with automatic samplers or spectrophotometric probes (Gruber et al. 2006). Both approach are challenging to implement, and the data are often difficult to interpret because of systematic and random errors, often due to sensor fouling (Ort and Gujer 2006). Interestingly, there has been recent progress on non-contact pollution monitoring in wastewater.

So far, all the research groups used spectrometers to measure diffuse reflectance of wastewater samples in laboratories, and established correlations with COD and suspended solids (Agustsson et al. 2014; Xing et al. 2019) . Unfortunately, in real-world applications, external factors such as floating objects, direct light reglection, water depth and waves structure will influence the measurement. In this paper, we investigate for the first time how non-contact monitoring could be improved by hyperspectral imaging (HSI). This is a standard method for remote sensing of natural water bodies (Stuart, McGonigle, and Willmott 2019). However, to the best of our knowledge, it has not been applied for sewer wastewater pollution monitoring.

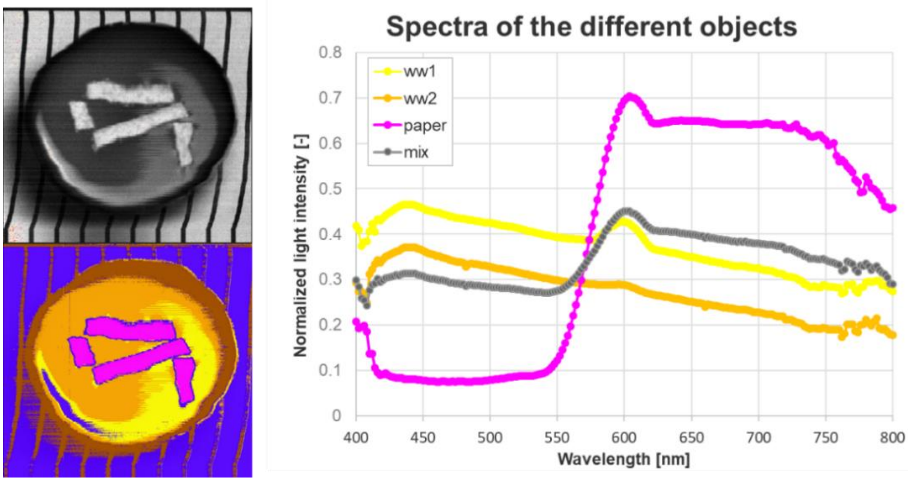

Figure 1: Pixel classification implemented with hyperspectral data to extract the wastewater reflection spectrum

In comparison to spectrometers, hyperspectral cameras can better deal with the sewer variability, because they measure simultaneously spectral and spatial data. Results from perliminary trials (Figure 1) demonstrate how a pixel classification can be implemented to isolate the spectra of wastewater (yellow and orange) from paper pieces (magenta), the cup borders and the background. In a similar way, the spatial information can be used to take into acount the influence of other external factors.

In the future, pollution monitoring in the drainage system will contribute to improving the overall efficiency of urban water management, and therefore minimizing our impact on the environment. The emergence of new technologies, such as hyperspectral imaging, are promising. In this contribution, we will present the state of the art of non-contact monitoring of wastewater and share our current research. Specficially, we will present an experimental setup, data-processing approach and results.

Experimental laboratory setup for diffuse light reflection measurement

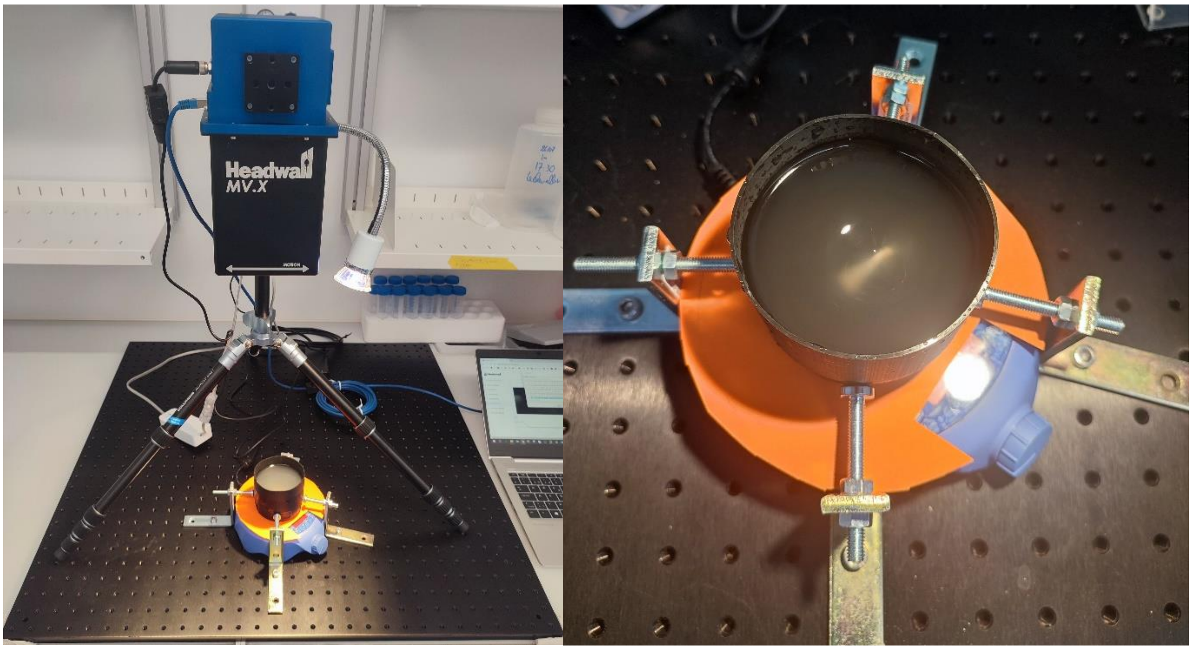

Figure 2: Experimetal setup for hyperspectral image aquisition

The non-contact monitoring concept has been tested in laboratories. Sewer wastewater samples were taken at the inlet of the primary decanter of a wastewater treatment plant. Dilution and mixing of 8 raw samples sampled at different times of the day, as well as the addition of a formazine turbidity standard, made it possible to generate a total of 144 wastewater samples. The raw samples were analysed with cuvette tests LCK314 for chemical oxygen demand (COD), LCK350 for orthophosphat (PO4-P), LCK303 for ammonium (NH4-N), with Ionenchromatography for phosphate and sulfate, with a Hach TL2300 for turbidity, with flow injection analysis photometrie for ammonium and with TOC-L analyser for dissolved organic carbon and total dissolved nitrogen. In addition, absorbtion spectra between 320 and 1000 nm were aquired with a Hach DR3800 spectrophotometer. The parameter used for further analysis are presented in Table 1.

Table 1: Wastewater pollution parameter range

	COD [mg/L]	Turbidity	NH4-N [mg/L]	PO4-P [mg/L]
Range	93 - 379	22 - 267	10 - 25	1.2 – 2,3

For the image acquisition, 200mL of each samples was placed in black cups. A picture of the setup is presented in figure 2. A magnetic stirrer ensured the stability of the suspended solids. A halogen light was used to illuminate the samples. The camera to aquire hyperspectral images is a MV.X. system from Headwall Photonics. It is able to measure 1020 spatial bands and 300 wavelength between 400 and 888nm. The camera was previously optically calibrated with a grey calibration target, and the distance with the sample was determined by the focal distance of the lense.

Data pre-processing and analysis

To extract the diffuse reflection spectra from each hyperspectral acquisition, the PerClass Mira software was used. First, the different areas of few images were manually labelled. Based on these informations, PerClass Mira automatically labelled the pixels of all the images. Figure 1 is an example of the result of this procedure. Finally, the mean spectra of all the pixels corresponding to the diffuse reflectance was calculated as the diffuse reflectance spectra of each sample. The sklearn package of Python was used to create a data-driven model able to predict wastewater pollution from their reflectance spectra. After spectral normalization, a leave-one-out cross validation PLS model with 20 components was developped for each pollution parameter.

Results

So for, only the results of the cuvette tests (COD, orthophosphat and ammonium) and the turbidity values were used. The results of the leave-one-out PLS models are shown in the following table:

Table 2: results of the PLS regression

	COD [mg/L]	**Turbidity**	**NH4-N [mg/L]**	**PO4-P [mg/L]**
R^2	0.795	0.967	0.616	0.575
RMSE	30.3	12.2	1.9	0.2

Those first results are very promising. Similarely to other work, such as Agustsson et al. (R^2=0.95 for turbidity and 0.69 for COD), the turbidity prediction is very good, probably because the reflection of light directly depends on the amount of suspended particles. For COD, the prediction are similar to Agustsson as well, which is interesting given the fact that they had access to ultraviolet wavelength, which was not possible with the MV.X. camera. Xing et al. also very good COD prediction (R^2=0.95) without UV reflectance. An additionnal interesting result could therefore be to analyse the representative wavelength for the PLS model, to see how the UV is important in Agustsson's data.

There is as well a certain prediction potential for NH4 and PO4, despite the fact that NH4 or PO4 don't interact with visible light. A possible explanation is that ammoniumand phosphate are correlated to another component which is causing reflectance. It is interesting to note that ammonium and phosphate are correlated together (Pearson's p: =0.859), however they are not significantly correlated with COD or turbidity.

Further work before the conference:

The result have been obtained end July, and further analysis will be done in August. First, the full laboratory data will be investigated, including absorbance spectra, sulfate, total nitrogen and dissolved organic carbon. Second, other pre-processing methods (standard normal variate, linear and polynonial detrend) will be tested. Third, outlier detection will be implemented. Finally, other data-driven approach, such as multi-linear regression, random forest or support vector machine will be explored.

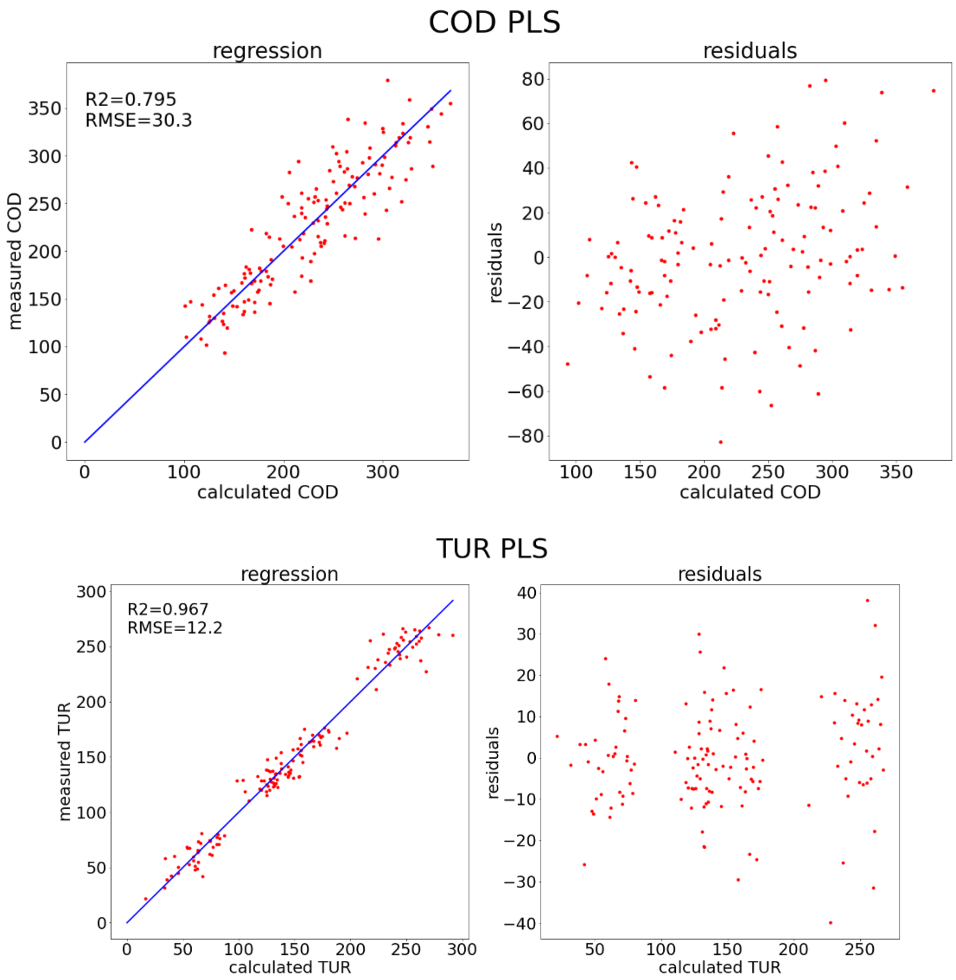

Figure 3: result of the LOO-PLS regression for COD and turbidity

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References

Agustsson, J., O. Akermann, D. Barry, and L. Rossi. 2014. 'Non-Contact Assessment of COD and Turbidity Concentrations in Water Using Diffuse Reflectance UV-Vis Spectroscopy.' *Environmental Science. Processes & Impacts* 16 8: 1897–1902. https://doi.org/10.1039/c3em00707c.

Gruber, G., J.-L. Bertrand-Krajewski, J. De Beneditis, M. Hochedlinger, and W. Lettl. 2006. 'Practical Aspects, Experiences and Strategies by Using UV/VIS Sensors for Long-Term Sewer Monitoring'. *Water Practice and Technology* 1 (1): wpt2006020. https://doi.org/10.2166/wpt.2006.020.

Huang, Danping, Jianqiu Ye, Shaodong Yu, Ying Tian, Xiaomei Wen, Yiqi Wang, Luotong Ren, and Xiaoguang Chen. 2022. 'Study on a Fast Non-Contact Detection Method for Key Parameters of Refractory Organic Wastewater Treatment'. *Biochemical Engineering Journal* 177 (January): 108269. https://doi.org/10.1016/j.bej.2021.108269.

Ort, C., and W. Gujer. 2006. 'Sampling for Representative Micropollutant Loads in Sewer Systems'. *Water Science and Technology* 54 (6–7): 169–76. https://doi.org/10.2166/wst.2006.591.

Pistocchi, A. 2020. 'A Preliminary Pan-European Assessment of Pollution Loads from Urban Runoff'. *Environmental Research* 182 (March): 109129. https://doi.org/10.1016/j.envres.2020.109129.

Stuart, McGonigle, and Willmott. 2019. 'Hyperspectral Imaging in Environmental Monitoring: A Review of Recent Developments and Technological Advances in Compact Field Deployable Systems'. *Sensors* 19 (July): 3071. https://doi.org/10.3390/s19143071.

Xing, Zheng, Junying Chen, Xiao Zhao, Yu Li, Xianwen Li, Zhitao Zhang, Congcong Lao, and Haifeng Wang. 2019. 'Quantitative Estimation of Wastewater Quality Parameters by Hyperspectral Band Screening Using GC, VIP and SPA'. *PeerJ* 7 (December): e8255. https://doi.org/10.7717/peerj.8255.