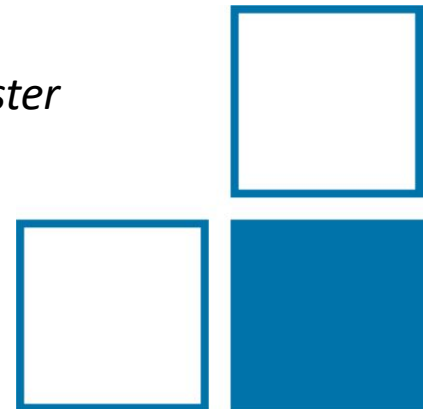


Joint regression and compressed sensing for chemical mapping in nano-FTIR

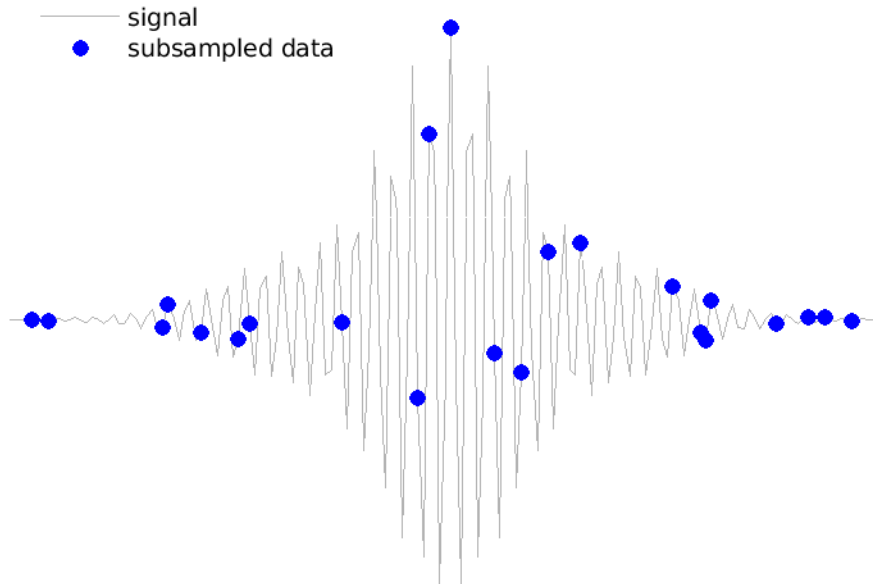
G. Wübbeler, M. Marschall, E. Rühl, B. Kästner, & C. Elster



Content

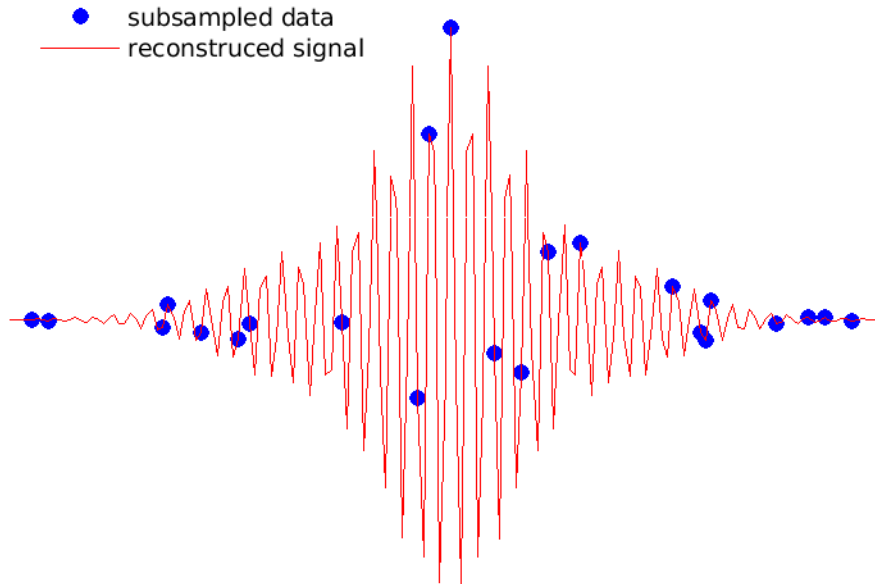
- **Compressed sensing**
- **Joint regression and compressed sensing**
- **Application to Nano-FTIR**
- **Summary**

Compressed sensing



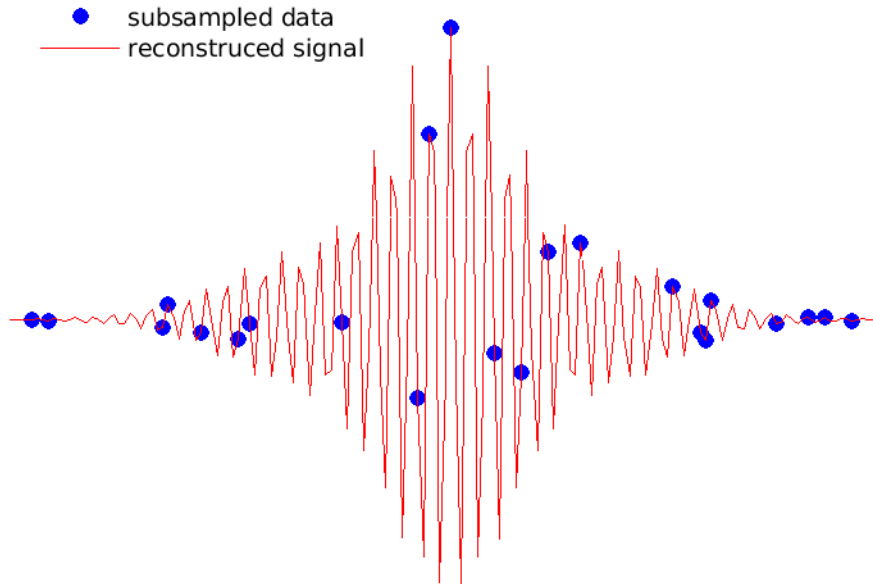
Goal: signal reconstruction given randomly subsampled data

Compressed sensing



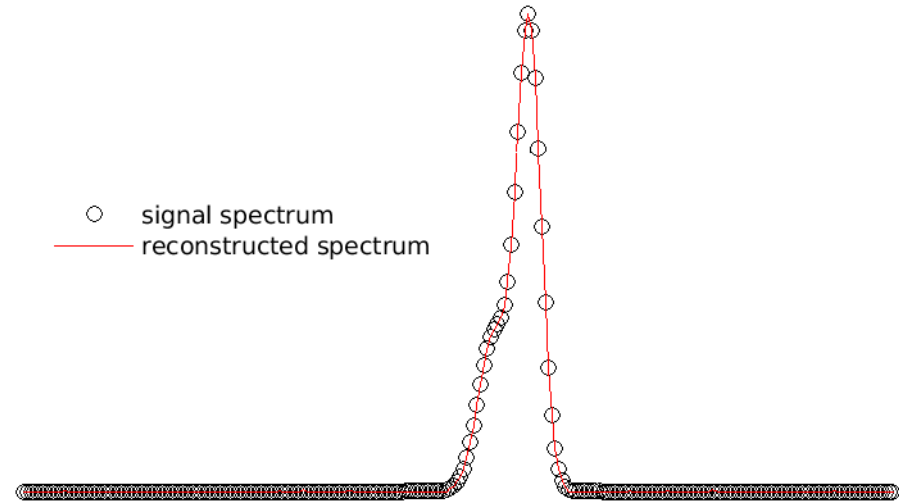
Compressed sensing reconstruction

Compressed sensing



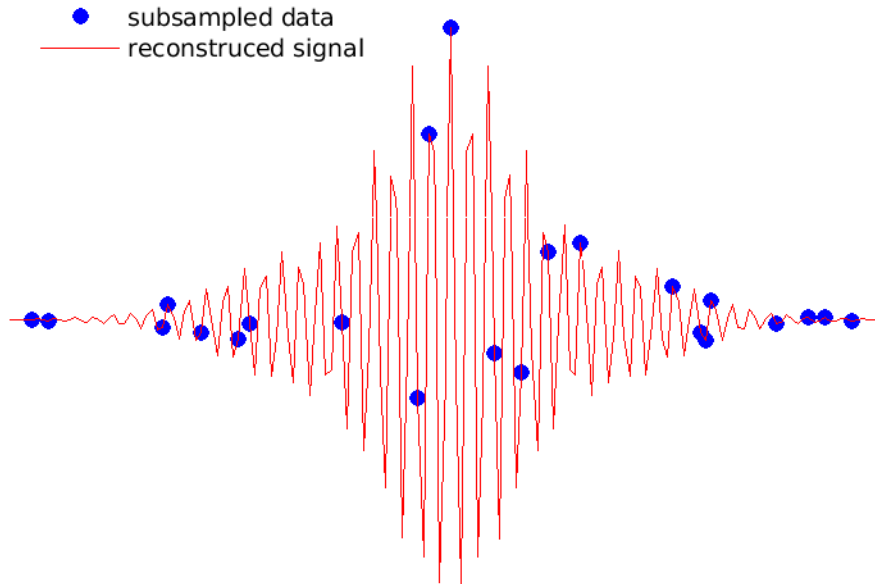
Compressed sensing reconstruction

Fourier domain



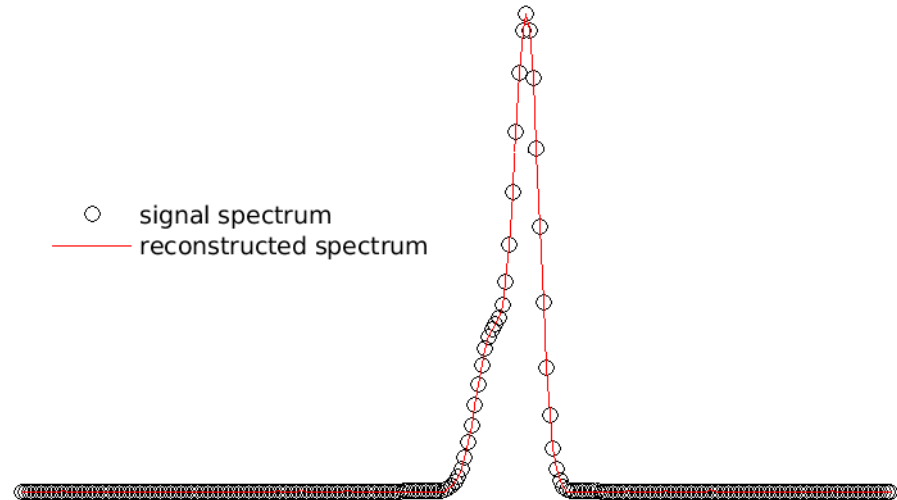
Only few non-zero Fourier coefficients

Compressed sensing



Compressed sensing reconstruction

Fourier domain



Only few non-zero Fourier coefficients



Signal is sparse in Fourier domain

Compressed sensing: Math

Sparse recovery from an underdetermined linear system

$$\min_{\mu} \|\mu\|_0 \quad \text{subject to} \quad y = V\mu$$

y	subsampled data
V	known sensing matrix
μ	sought sparse vector
$\ \mu\ _0$	number of non-zero elements

Compressed sensing: Math

Sparse recovery from an underdetermined linear system

$$\min_{\mu} \|\mu\|_0 \quad \text{subject to} \quad y = V\mu$$

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Solution via combinatorial search usually not tractable

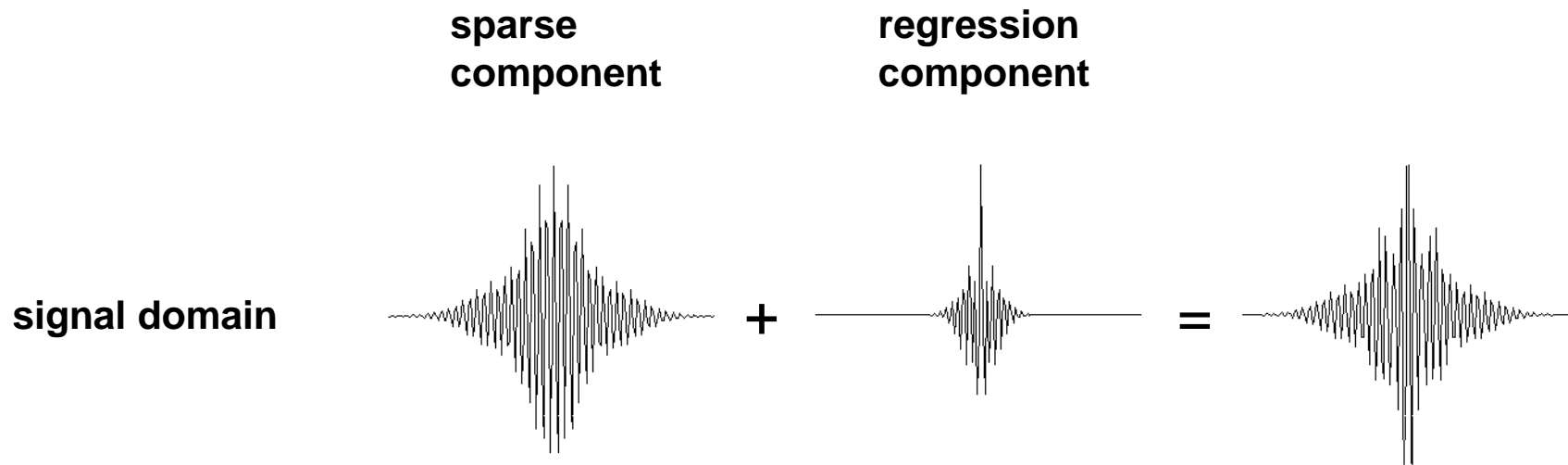
- Convex relaxation : $\min_{\mu} \|\mu\|_1$ subject to $y = V\mu$
- Alternative: Greedy methods

Donoho, D. L. (2006). Compressed sensing. *IEEE Transactions on information theory*, 52(4), 1289-1306.

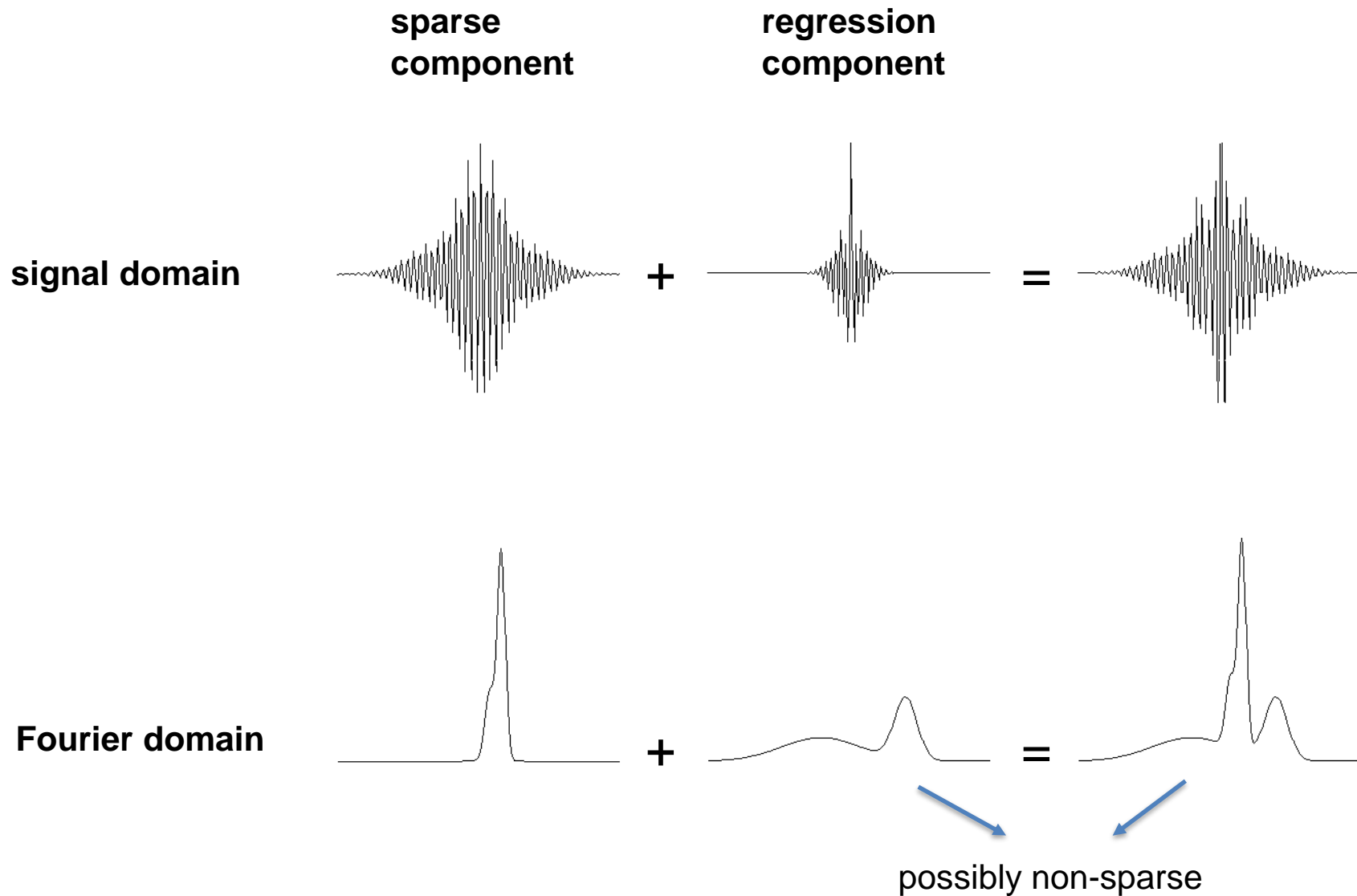
Candes, E. J. (2008). The restricted isometry property and its implications for compressed sensing. *Comptes rendus mathematique*, 346(9-10), 589-592.

Eldar, Y. C., & Kutyniok, G. (Eds.). (2012). Compressed sensing: theory and applications. Cambridge University Press.

Joint regression and compressed sensing



Joint regression and compressed sensing



Joint regression and compressed sensing

Model

$$y = V\mu + X\theta$$



**sparse
component**



**regression
component**

y

subsampled data

V

known sensing matrix

μ

sought sparse vector

X

known design matrix

θ

sought weights (few)

Joint regression and compressed sensing

Model

$$y = V\mu + X\theta$$

**sparse
component**

**regression
component**

y

subsampled data

V

known sensing matrix

μ

sought sparse vector

X

known design matrix

θ

sought weights (few)

Two step procedure

1) Evaluation of sparse signal

- Determine matrix P so that $PX = 0$
- $\tilde{y} = Py = PV\mu$ represents standard compressed sensing task
- Apply greedy method to obtain sparse representation

Joint regression and compressed sensing

Model

$$y = V\mu + X\theta$$



**sparse
component**



**regression
component**

y

subsampled data

V

known sensing matrix

μ

sought sparse vector

X

known design matrix

θ

sought weights (few)

Two step procedure

2) Regression

- Reduced regression task $y = \tilde{V} \tilde{\mu} + X\theta$

\tilde{V} : matrix containing only columns of V where $\mu \neq 0$

- Identifiable since $\text{rank}([\tilde{V}, X]) = p + r$

p

number of weights θ

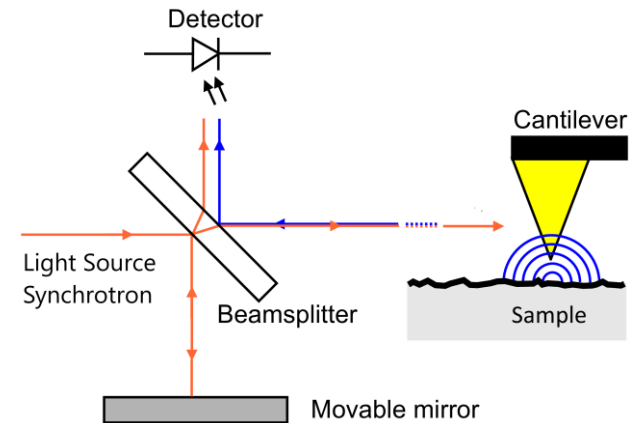
r

number non-zero elements of μ

→ Estimated weights θ and coefficients $\tilde{\mu}$

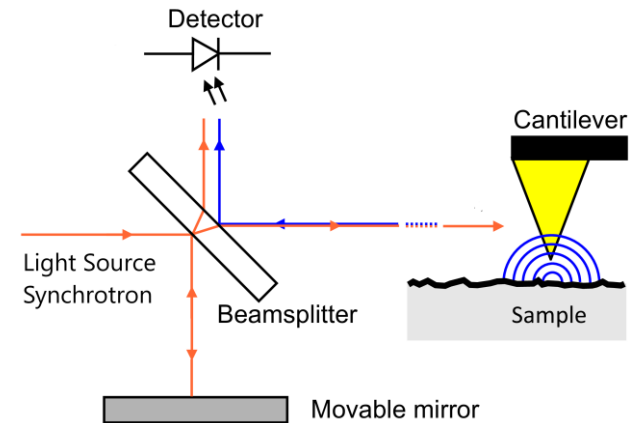
Nano-Fourier-transform infrared spectroscopy (nano-FTIR)

- Combines infrared (IR) spectroscopy with scanning probe microscopy.
- Enables hyperspectral imaging at nanometer spatial resolution



Nano-Fourier-transform infrared spectroscopy (nano-FTIR)

- Combines infrared (IR) spectroscopy with scanning probe microscopy.
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Nano-FTIR can be used to determine **chemical mappings**

- Spatial distribution of concentration of substances contained in the sample
- Obtained by solving a regression task using known spectral characteristics

Huth F, Govyadinov A, Amarie S, Nuansing W, Keilmann F and Hillenbrand R (2012) Nano-FTIR absorption spectroscopy of molecular fingerprints at 20 nm spatial resolution *Nano Lett.* **12** 3973–8

Amarie S, Zaslansky P, Kajihara Y, Griesshaber E, Schmahl W W and Keilmann F 2012 Nano-FTIR chemical mapping of minerals in biological materials *Beilstein J. Nanotechnol.* **3** 312–23

Nano FTIR chemical mapping

Challenges

- Nano-FTIR is scanning based → long measurement times (hours)
- Data may contain signal contributions of further, unknown substances

Nano FTIR chemical mapping

Challenges

- Nano-FTIR is scanning based → long measurement times (hours)
- Data may contain signal contributions of further, unknown substances

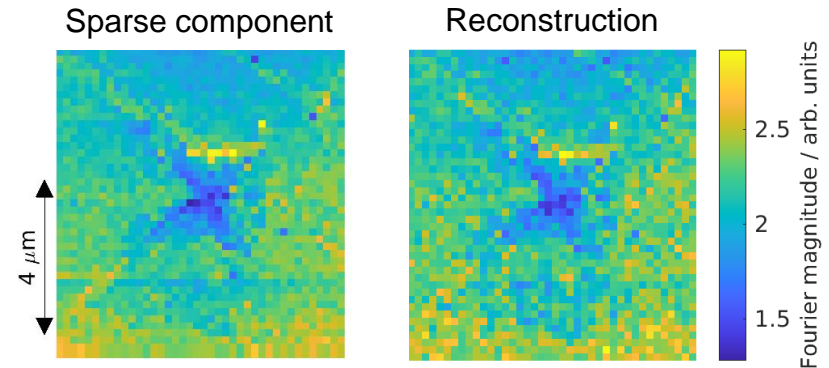
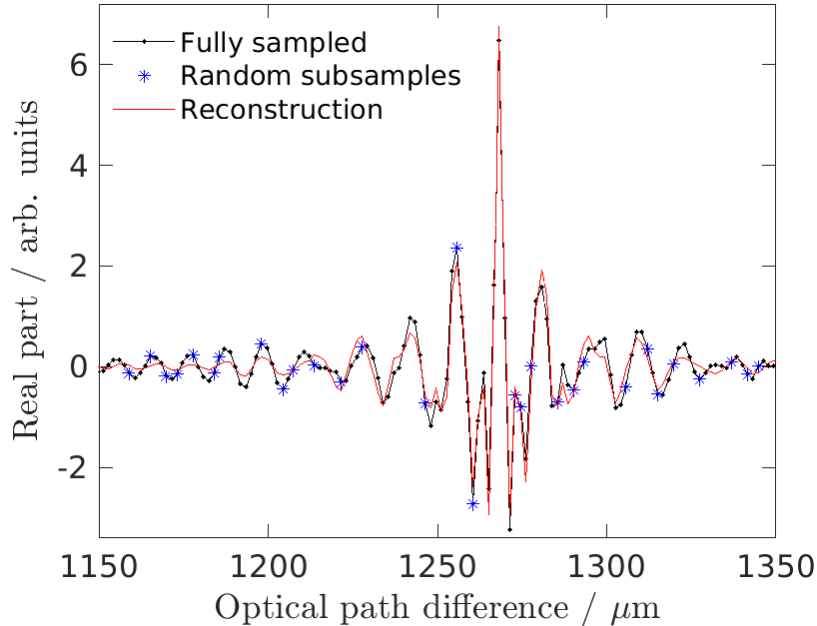
Joint regression and compressed sensing approach

- Subsampling enables reduced measurement times
- Additional signal contribution is assumed to be sparse
- Spatial regression includes Gaussian Markov random field regularization

Rue, H., & Held, L. (2005). Gaussian Markov random fields: theory and applications. Chapman and Hall/CRC.

Nano FTIR reconstruction

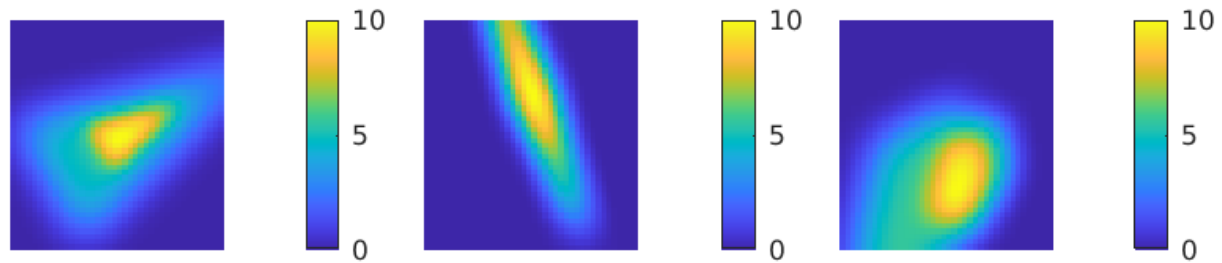
- Real nano-FTIR measurements^{*)} superimposed by simulated chemical mappings
- Simulated components and sparse signal exhibit spectral overlap
- Data taken at a subsampling rate of 20%.



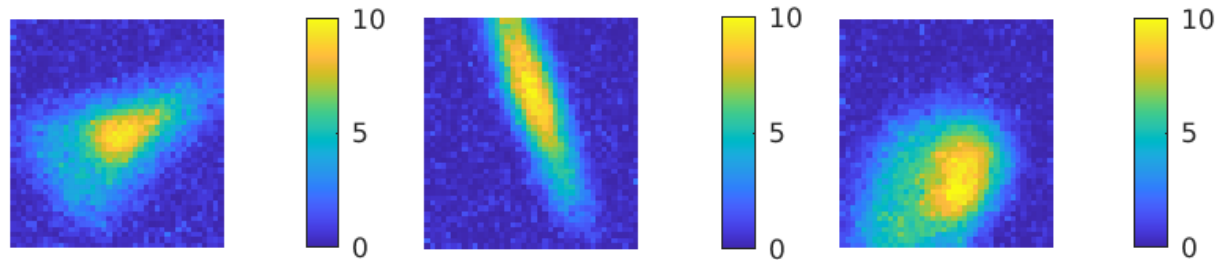
*) Kästner, B., Schmähling, F., Hornemann, A., Ulrich, G., Hoehl, A., Kruskopf, M., Pierz, K., Raschke, M. B., Wübbeler, G. and Elster, C. (2018) Compressed sensing FTIR nano-spectroscopy and nanoimaging. Optics Express, vol. 26, no. 14, pp. 18115-18124.

Chemical mapping estimates

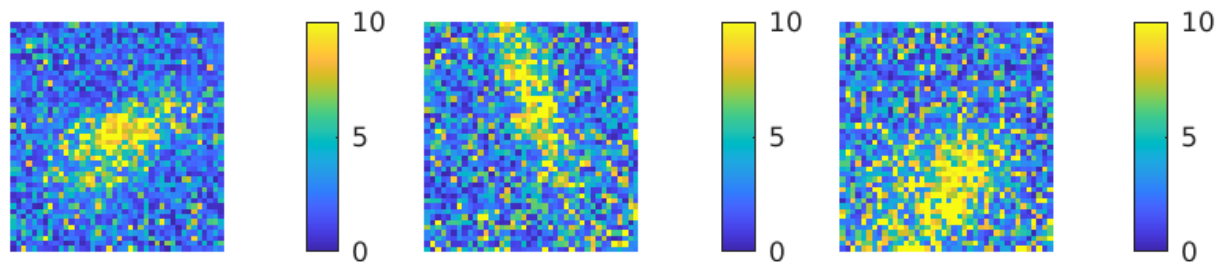
Simulated mappings



Joint regression and compressed sensing



Naïve regression,
sparse signal treated
as error



Summary

- **Development of a joint regression and compressed sensing approach**
- **Subsampling enables reduced measurement times**
- **Unknown signal contributions modelled non-parametrically**
- **Functionality demonstrated using augmented nano-FTIR data**

Wübbeler, G., Marschall, M., Rühl, E., Kästner, B., & Elster, C. (2022). Compressive nano-FTIR chemical mapping. *Measurement Science and Technology*, 33(3), 035402.