Thermal characterisation by Scanning Photothermal Radiometry using a random undersampled measurement scheme

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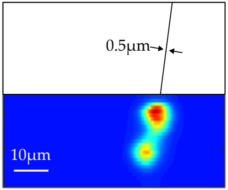
Context

Scanning Photothermal Radiometry

Very **precise** (0.5 µm)

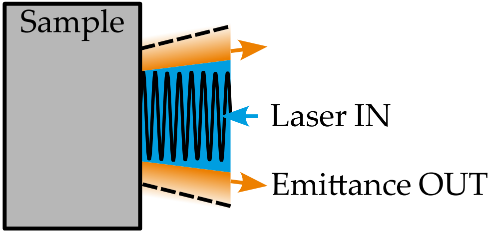


But quite **slow** (1 h per image)

In this presentation: Acceleration of $\sim 6\times$ using undersampling techniques

Summary

Modulated Photothermal Radiometry (MPtR)

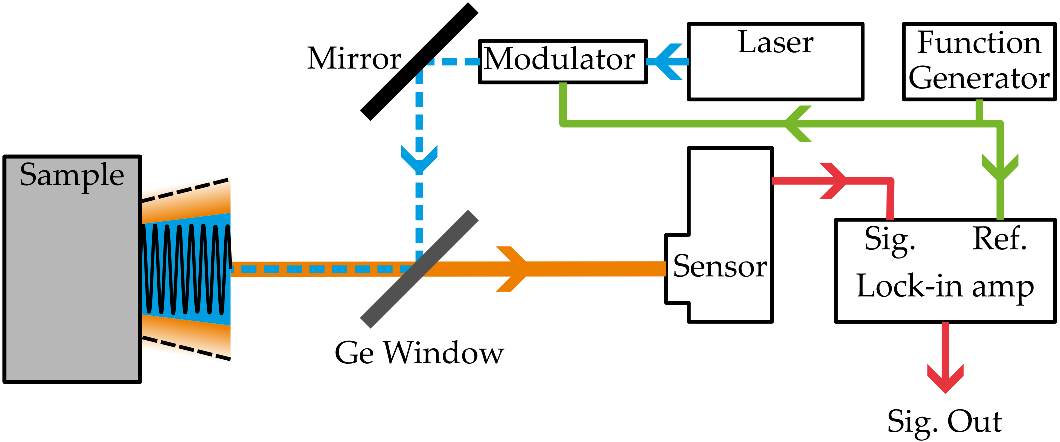


Stefan-Boltzmann law
$M = \epsilon \sigma T^4$

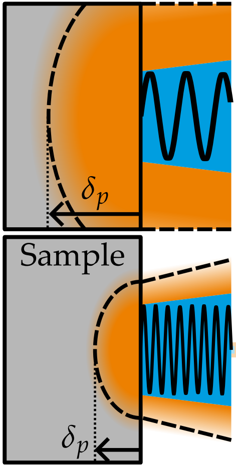
For input periodic laser heating
$I_{laser} = A\cos(2\pi f t)$

And small ΔT
$\Delta M \simeq 4\epsilon\sigma T_0^3 \Delta T_f \cos(2\pi f t + \phi)$

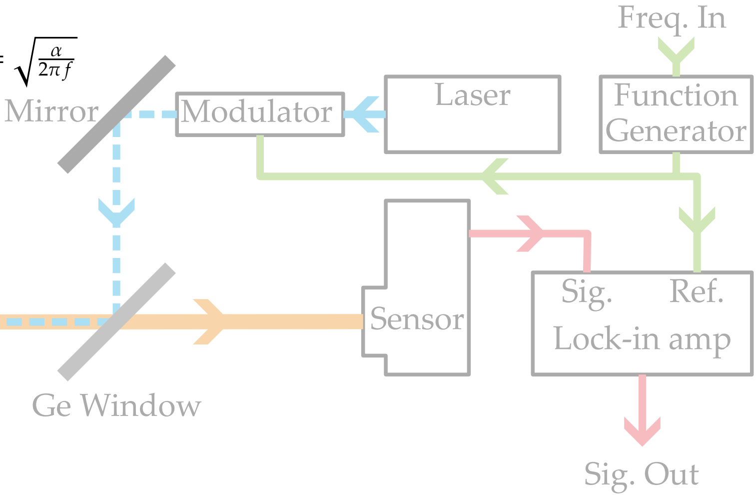
Modulated Photothermal Radiometry (MPtR)



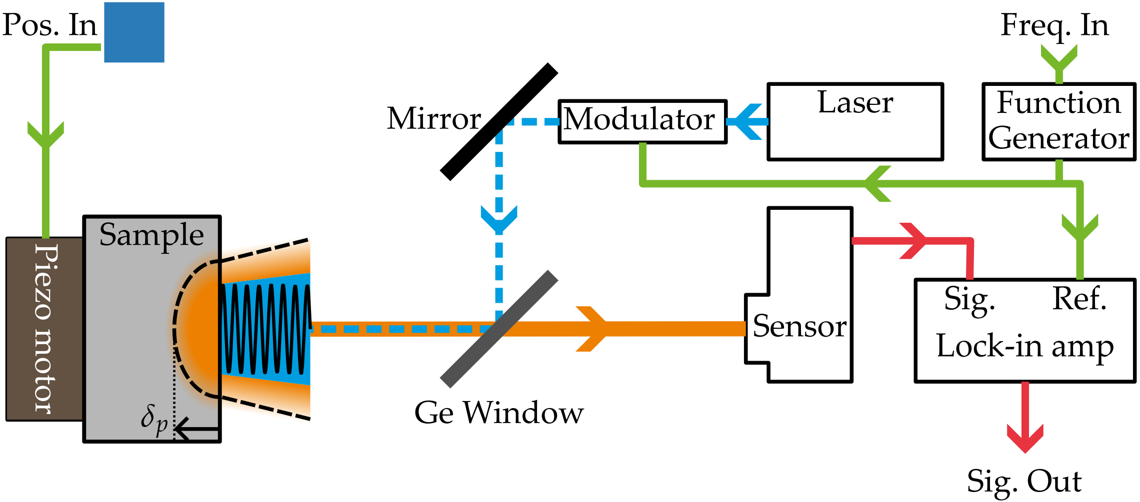
MPtR Frequencies



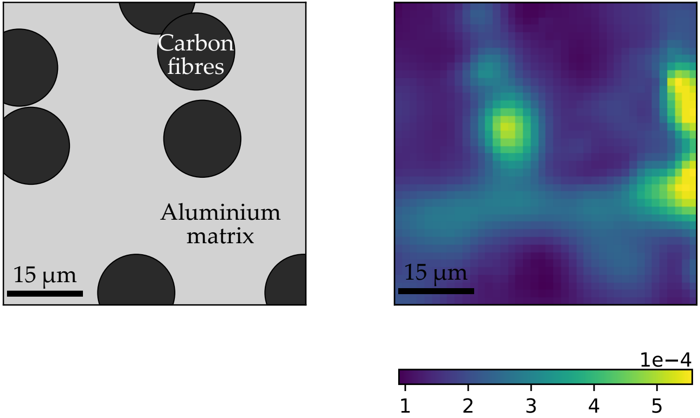
$$\delta_p = \sqrt{\frac{\alpha}{2\pi f}}$$



Scanning Photothermal Radiometry



Sample studied: Carbon fibre - Aluminium matrix



(a) Schematic (b) Amplitude (a.u.)

Figure: Reference image 40x40 points (1600) @ 6kHz, time ~ 1h

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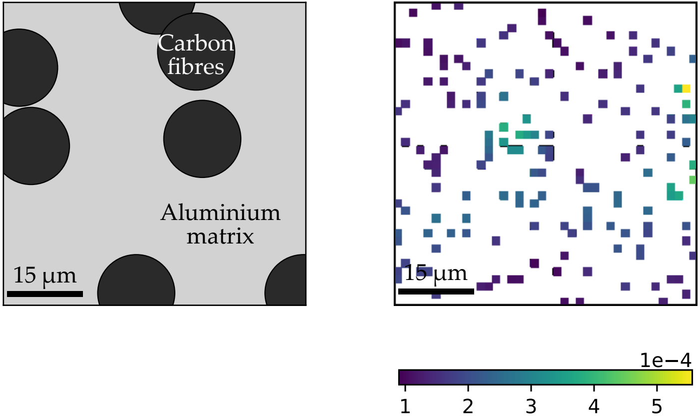


(a) Schematic (b) Amplitude (a.u.)

Figure: 160 random points within 40x40 (1600) @ 6kHz, time ~ 10min

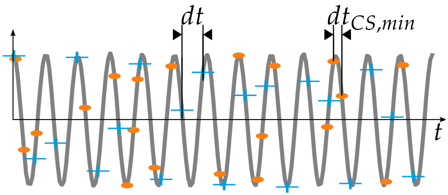
Compressive Sensing

Objective:

Solve an inverse problem $y = Hx$
With basis change $x = \Psi\xi$
And ξ sparse

Minimising using a ℓ_1-norm promotes sparsity
(ie. sets values to 0)

$$\hat{\xi} = \min_{\xi} ||H\Psi\xi - y||_2 + \lambda||\xi||_1$$



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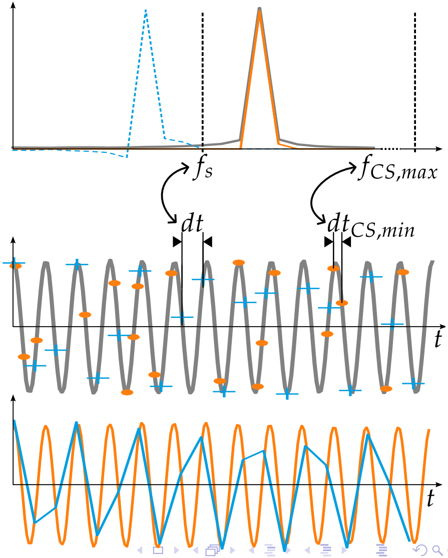
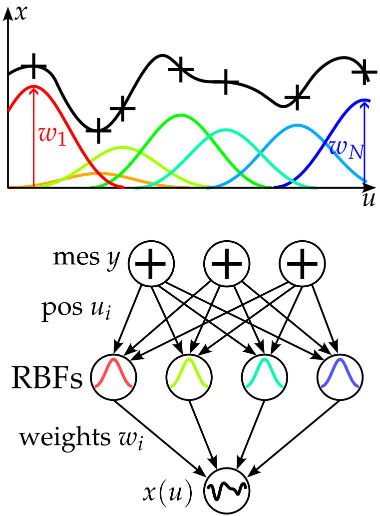


Radial Basis Functions interpolation



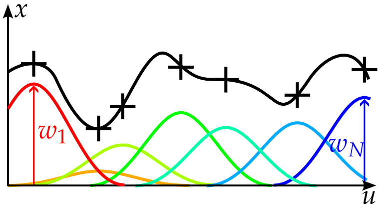
Objective:

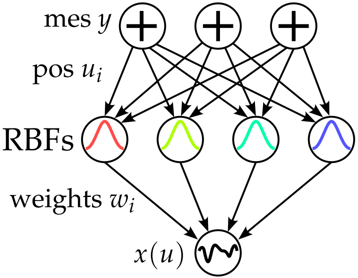
Find x from a set of measurements y at known positions u_i ie. $y_i = x(u_i)$

$$y = \begin{pmatrix} A(|u_1 - u_1|) & A(|u_2 - u_1|) & \cdots & A(|u_N - u_1|) \\ A(|u_1 - u_2|) & A(|u_2 - u_2|) & \cdots & A(|u_N - u_2|) \\ \vdots & \vdots & \ddots & \vdots \\ A(|u_1 - u_N|) & A(|u_2 - u_N|) & \cdots & A(|u_N - u_N|) \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \end{pmatrix}$$

Find weights w_i, then $x = \sum w_i A(|u - u_i|)$

Radial Basis Functions interpolation





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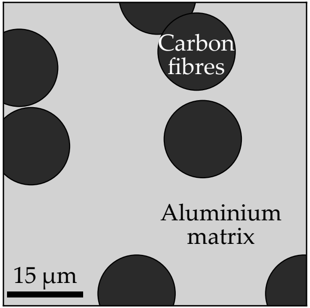
RBF Interpolation

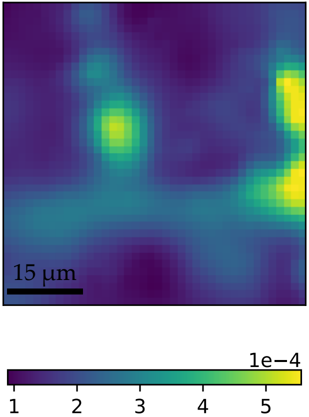
$$y = \mathbf{A}w$$

RBF Approximation

$$y = (\mathbf{A} + \lambda \mathbf{I})w$$



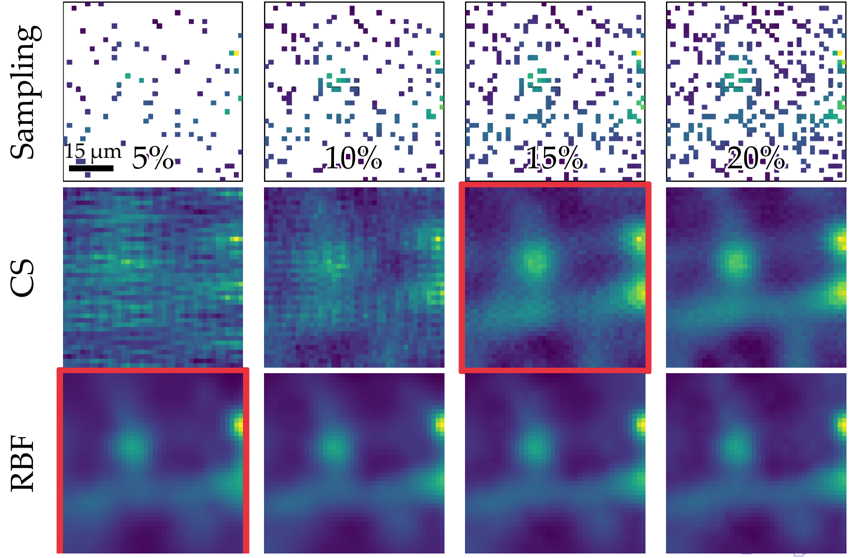
(a) Schematic



(b) Amplitude (a.u.)

Figure: Reference image 40x40 points (1600) @ 6kHz, time ~ 1h

Sampling ratios



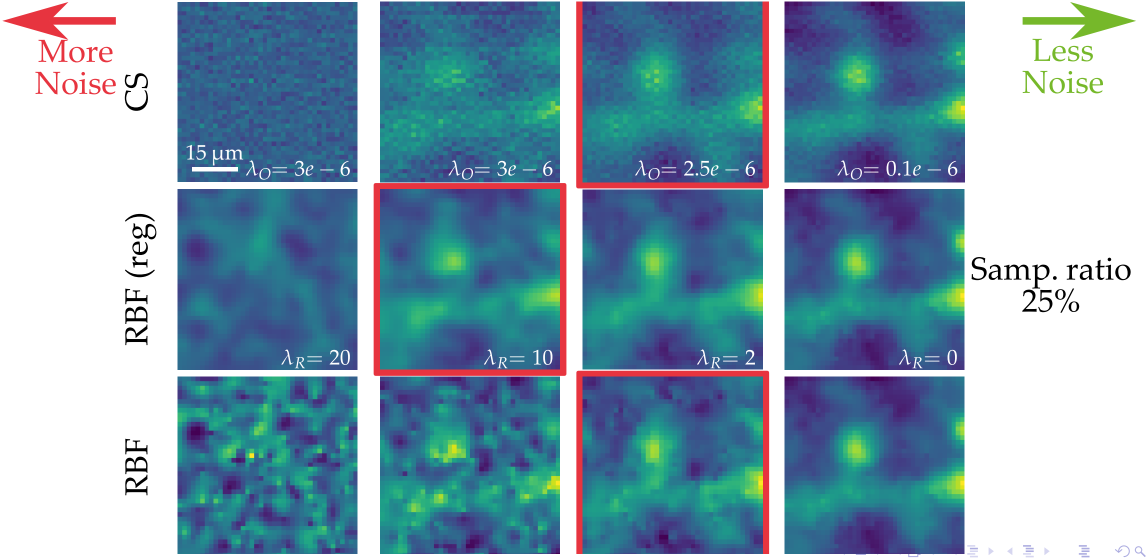
Sampling ratios

In this study:

- Both methods allow for a significant reduction in the number of points
- RBF is better in this application

Is this still true with noisy data?

Noise levels



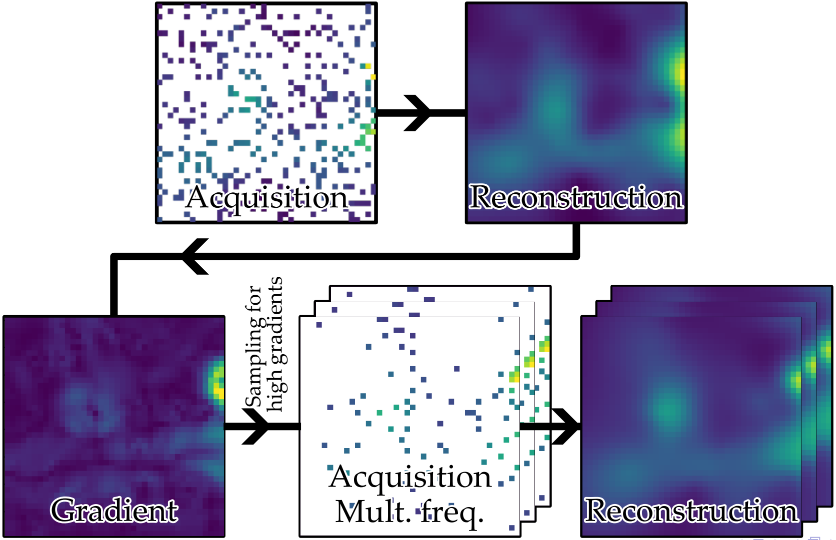
Noise levels

In this study:

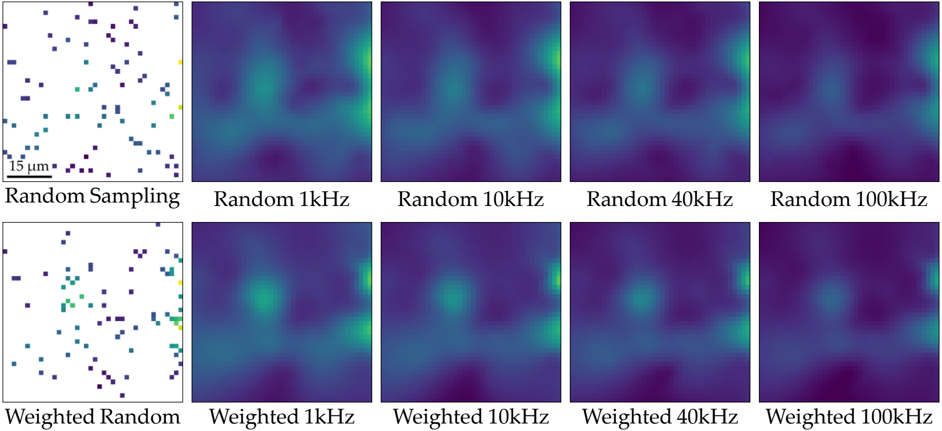
- All methods are quite sensitive to noise
- Adding a regularisation parameter to the RBF problem helps with denoising

Now, can we use this gain of time to scan at multiple frequencies?

Multiple frequencies scan



Multiple frequencies scan



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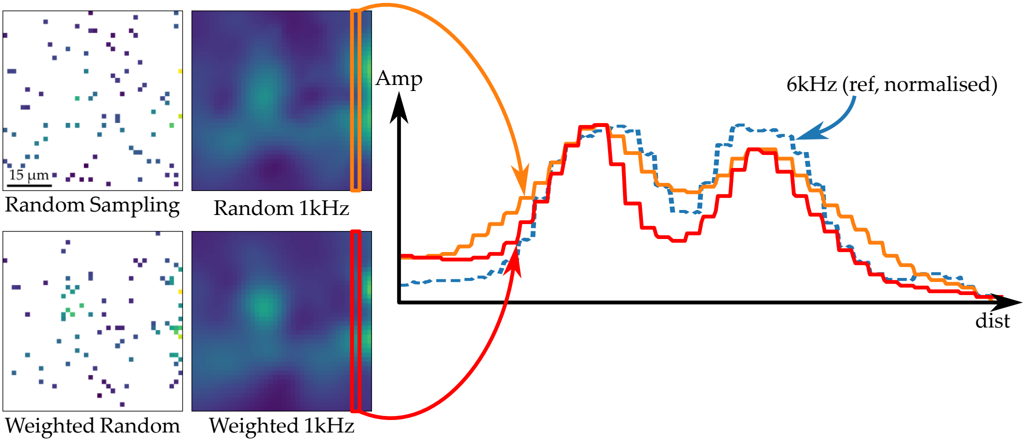

Conclusion

For 1 frequency, 50×50 image: $1\text{h} \longrightarrow 10\text{min}$

For 10 frequencies, 50×50 image: $10\text{h} \longrightarrow 1\text{h}40$ (Detector autonomy of $\sim$ 8h)

Applicable to a lot of point-by-point methods[1]

[1] Smoother images are usually better

Conclusion

Thank you!

Any questions?

See the QIRT program for the article