Block Sparse Bayesian Learning for Plasma Optical Emission Spectral Analysis

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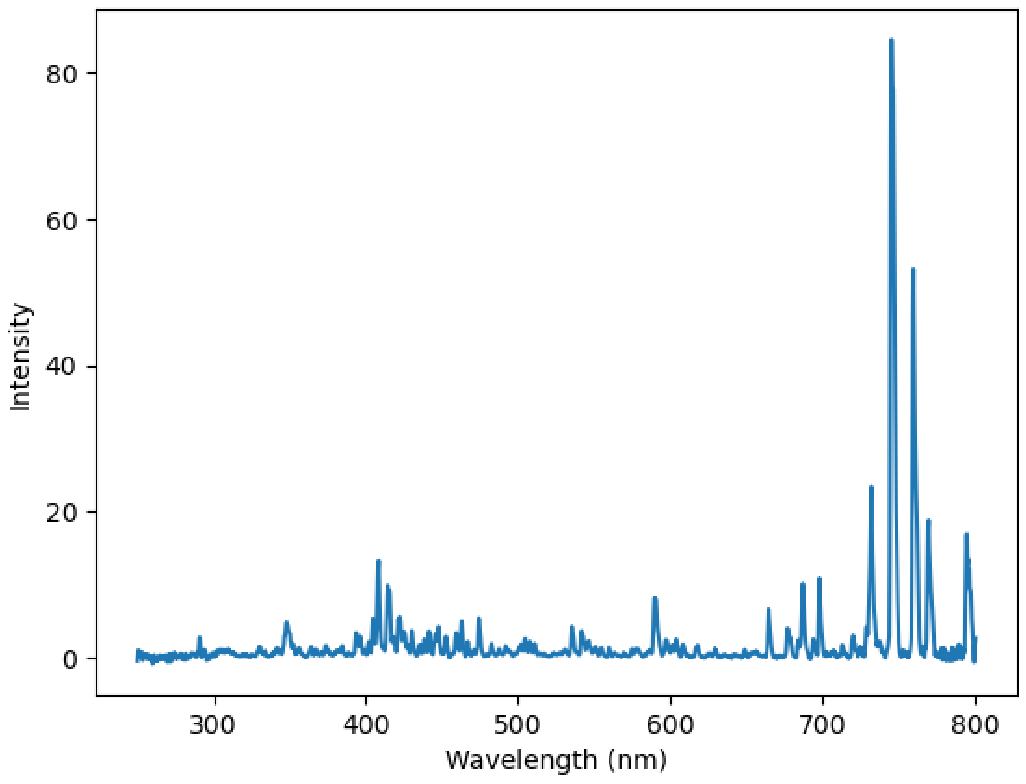
Background & Aims

Plasma Optical Emission Spectra can be used to analyze vacuum processes. Specifically, what is the gas composition within the sealed environment during vacuum deposition for thin film coating. This analysis would be performed on real time data streams.

Important aspects of this analysis are being robust to noise, whilst being able to detect low magnitude spectral peaks. Detecting these low order peaks can be crucial, as they could be indicative of an error in the system

A mathematical system that exploits the characteristics of the problem is required. Firstly, we obtain a theoretically sparse measurement vector that has some noise. There is also a spectral database that contains all the positions and amplitudes of the peaks for all ionizations of an element or molecule. This database can be represented as a sparse basis matrix. Moreover, there is a gas composition state space that comprises of many ionizations of the same element. Thus, the state vector is a concatenation of sub-vectors where each sub-vector relates to all the ionizations of a molecule.

Therefore, we can use the **Block Sparse Bayesian Learning**[1] framework to solve our gas composition. The BSBL framework solves a compressed sensing problem[2] (noisy matrix-vector problem), where the state vector to be solved is clustered.



$$\mathbf{y} = \mathbf{D}\mathbf{x} + \mathbf{e}, \quad \mathbf{x} = [x_1, ..., x_{d_1}, ..., x_{d_{g-1}+1}, ..., x_{d_g}]^T$$
$$= [\mathbf{x}_1, ..., \mathbf{x}_g]^T$$

Current work

Currently, we are testing Block Sparse Bayesian Learning – Bound Optimisation on both synthetically generated spectra and industrial POES data. The algorithm can calculate the state vector effectively and is robust to noise, however it is very slow relative to the data stream.

BSBL –BO
The algorithm wants to maximise the posterior $p(\mathbf{x}|\mathbf{y};\sigma,\gamma,\mathbf{B})$. It does this by calculating a cost function. The cost function consists of a convex and concave function, so an upper bound of the concave function is calculated then the function is minimised.

Parallelization Of BSBL-BO
The algorithm performs most of the calculations for each block without dependance on another block.
However, there are a couple of equations that depend on global variables. Therefore, we look to mathematical representations of these variables that will enable parallelisation.

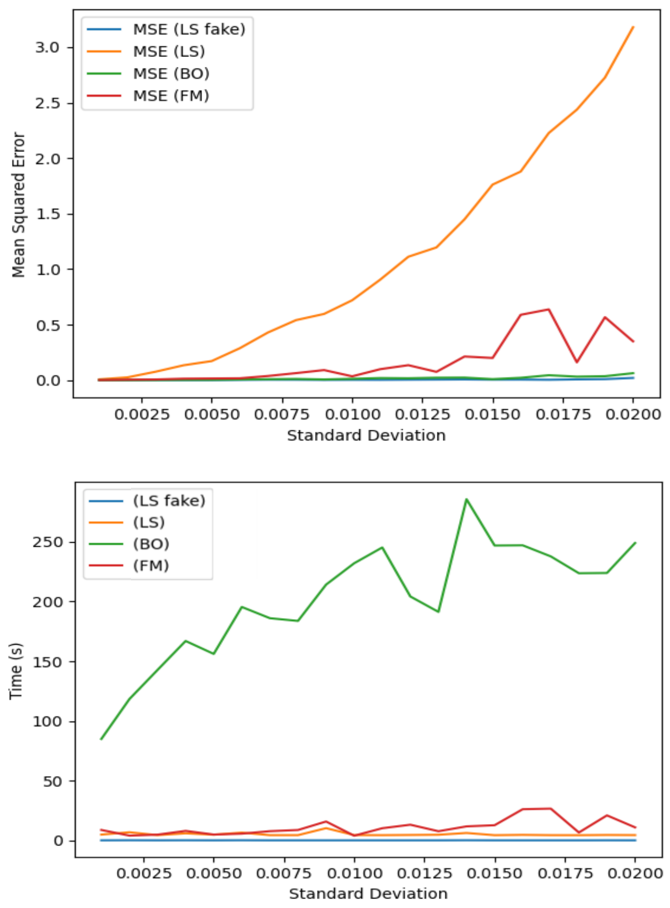
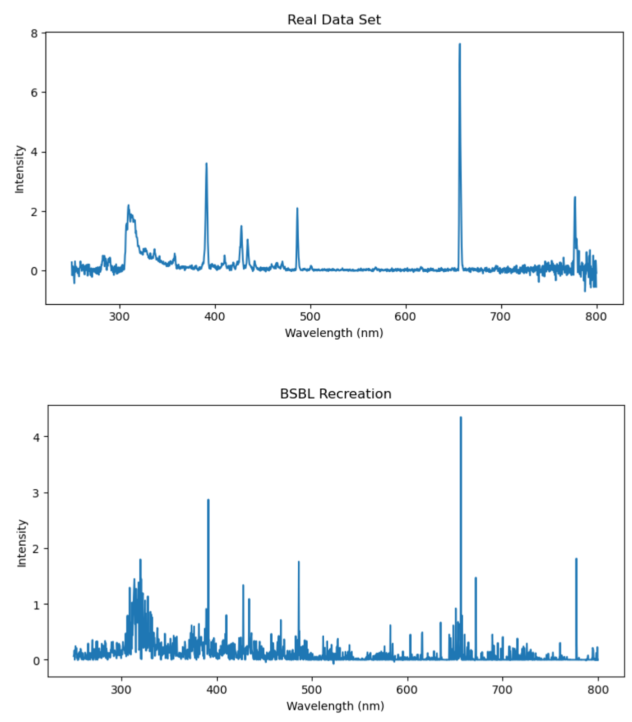


FIG 1: Mean Square Error and time taken of BSBL-BO, BSBL-FM [3] and least squares to calculate the state vector of synthetic spectra with increasing noise.

Industrial Results



Element/ Molecule	Maximum Value	Values
H	4.345	4.345
N2+	2.939	2.939, 0.357
O	1.812	1.812, 0.392, 0.190, 0.178, 0.028
YCl	1.129	1.129

FIG 2: A noisy plasma optical emission spectra of an air leak from Gencoa dataset. A recreation of the spectra using BSBL – Bound Optimisation algorithm and the (top 4) elements composition in tabular form.

BSBL - Bound Optimisation Produces an element composition that returns the highest scores to elements that are present in the system (true positives). However, there are a lot of low order false positives that are detected.

Moreover, the time to calculate the element composition is too slow for the rate of the data stream.

Future Work

- **Parallelization of BSBL-BO:** Continue the parallelization work with aims to improve performance, accuracy and scalability to higher dimensions.
- **Sequential BSBL solvers:** Investigate BSBL algorithms that would exploit the sequential nature of the data.
- **Alternate BSBL Algorithms:** Other BSBL algorithms could also be effective at solving spectral analysis problems in parallel. Moreover, if the algorithms prove to not be effective then a novel one could be created.
- **Application:** Implementation of the software on Gencoa's 'Optix' systems.

Conclusion

This project explores the problem of spectral analysis by using Block Sparse Bayesian Learning algorithms. Moreover, parallelization of the algorithm to improve performance, accuracy and scalability.

References

[1] Zhang, Z. and Rao, B.D., 2013. Extension of SBL algorithms for the recovery of block sparse signals with intra-block correlation. *IEEE Transactions on Signal Processing*, *61*(8), pp.2009-2015.
[2] Elad, M., Figueiredo, M.A. and Ma, Y., 2010. On the role of sparse and redundant representations in image processing. *Proceedings of the IEEE*, *98*(6), pp.972-982.
[3] Liu, B., Zhang, Z., Xu, G., Fan, H. and Fu, Q., 2014. Energy efficient telemonitoring of physiological signals via compressed sensing: A fast algorithm and power consumption evaluation. *Biomedical Signal Processing and Control*, *11*, pp.80-88.

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