

PHOTONIC AND NANOMETRIC HIGH-SENSITIVITY BIO-SENSING

DELIVERABLE 3.2 [TUDO, M42] REPORT ON THE DEMONSTRATION OF HIGH- RESOLUTION MAGNETIC IMAGING WITH CS IN NV



HIGH-RESOLUTION MAGNETIC FIELD IMAGING WITH CS IN NV

Work Package 3

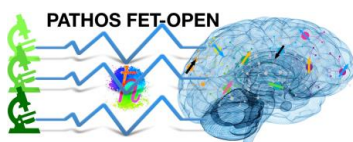
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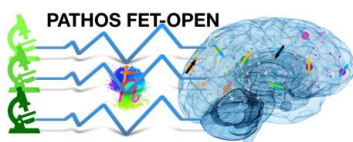
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1 Executive Summary

As deliverable D3.2 we report on our results of using nitrogen vacancy (NV) centers together with compressed sensing (CS) to achieve high-resolution magnetic sensing:

- We expand our previous work and improve our spectral resolution, together with high spatial resolution (confocal microscopy).
- **We improve our magnetic sensitivity and bandwidth by nearly an order of magnitude, at the price of only computational complexity.**
- Experimental results are being finalized for publication, and future directions, including enhanced CS with machine learning and time-dependent signal reconstruction are being pursued in collaboration with UNIFI and Weizmann.



2 Introduction and background

The essentials of compressed sensing and NV based magnetic sensing have been described in previous reports (D3.5, D3.6 and D3.1), and will not be repeated here.

As a brief recap and for completeness, we briefly mention the relevant aspects of these topics, which form the basis for the enhancements described in the following sections.

2.1 NV magnetic sensing

NV magnetic sensing is based on electron spin resonance (ESR), measured optically (sometimes referred to as optically detected magnetic resonance (ODMR)). The basic technique employed here relies on the change in fluorescence intensity of the NV as a function of its spin state, and the combination of fluorescence measurements with microwave driving (see Figure 1). By scanning the microwave (MW) field while illuminating the NVs, one can detect the driving of the NV spin states at the resonance transition frequencies. Since the NV spin resonances are magnetic field sensitive, the spectral positions of these resonances can be used to extract the magnetic field. The multiple

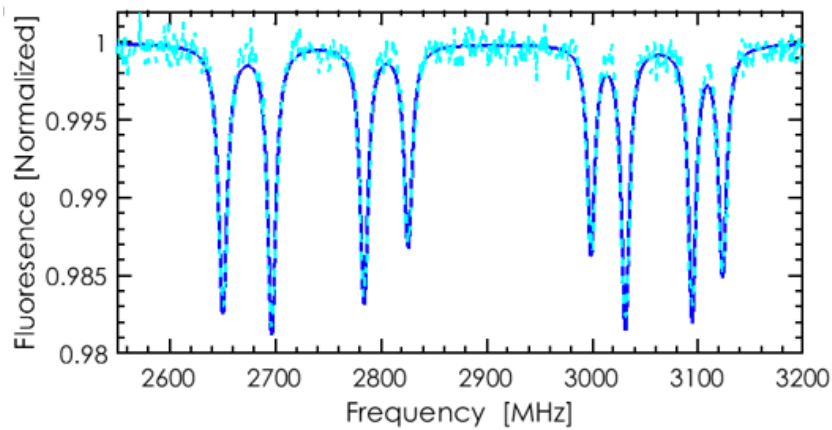


Figure 1: ESR spectrum of NV ensemble, 8 resonances correspond to $m_s = \pm 1$ spin transitions of each NV orientation in the diamond crystal.

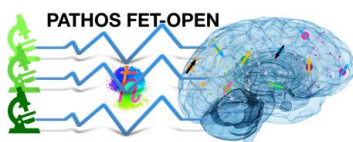
resonances are a result of the 4 different orientations of NVs in a single crystal diamond substrate.

The magnetic field sensitivity of such a measurement is usually defined through our accuracy in determining the spectral positions of the resonances translated into magnetic field, normalized by our measurement time:

$$\eta = \delta B \sqrt{T}$$

Where the magnetic field uncertainty δB depends on the noise in the measurement, which is reduced through averaging according to $\frac{1}{\sqrt{T}}$ (for uncorrelated measurements). The resulting sensitivity is given in units of $\frac{\text{Tesla}}{\sqrt{\text{Hz}}}$.

Practically, we scan in experiments the frequency of the applied MW drive by raster scanning, i.e., sequentially applying MW at different frequencies, usually with a constant spacing between frequency points. The resulting samples data is fit with a sum of Lorentzians, from which the centers of the resonances are extracted.



2.2 Compressed sensing in frequency space

Compressed sensing enables efficient measurements under the assumption that the data of interest is sparse in some basis. In our scenario of NV magnetic sensing, the data is a-priori sparse in frequency space using a Lorentzian function basis, since we're interested in finding the locations of 8 Lorentzians that span the resonance data (as seen in Figure 1). The 8 resonances are a results of the different NV orientations, and while the algorithm assumes this apriori, one can adjust the algorithm to account for a smaller number of resonances, which could occur as a result of specific orientations of the external bias field.

As detailed in D3.1, we define a discrete frequency space over which measurements can be taken, and iteratively apply the CS algorithm through repeated applications of random MW driving frequencies picked out from this space. We have shown that the simultaneous application of several driving frequencies produces optimized results, usually for approx. 3 concurrent frequencies (these frequencies are chosen randomly from the entire discrete frequency space).

We note that the CS algorithm does not necessarily converge, and therefore the measurement accuracy and resulting sensitivity must take this into account. We therefore define the success probability of the CS algorithm as p , and incorporate it into the sensitivity expression under the assumption that the measurement must be repeated in case it failed:

$$\eta = \delta B \sqrt{\frac{T}{p}}$$

As shown in Figure 2 (taken from D3.1 and explained in detail there), this technique allows us to improve our sensitivity compared to regular raster scanning (with sub-sampling).

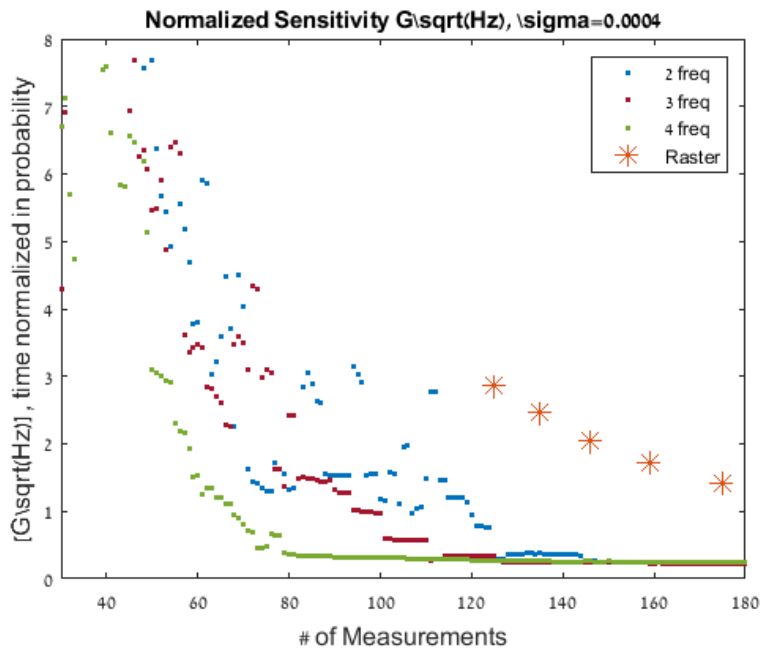
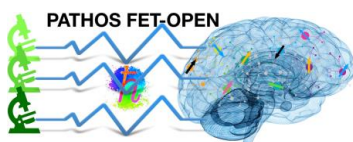


Figure 2: Comparison of magnetic sensitivity for raster scanning vs. CS. Sensitivity is plotted as a function of the number of measurements, simulated for a background field of $B = 120\text{G}$ and a measurement noise of 0.04%. The raster sub-sampling results are shown in red stars, while the CS is displayed as dots of different colors: blue for 2 simultaneous microwave frequencies, red for 3 frequencies and green for 4 frequencies (chosen randomly from the available discrete basis set).



3 Novel high-resolution CS technique and experimental results

We extend our previous results to enable high-resolution spectral reconstruction through an improved CS algorithm and realize this enhancement along with high-spatial resolution measurements in a confocal system.

3.1 Novel high-resolution CS algorithm

As described above, the CS algorithm in general defines a discrete space over which data is measured, and then reconstructed using a sparse basis in this discrete space.

This approach is strongly grounded in the optical origin of many CS algorithms, for which the discretized space naturally arises from the pixelated nature of the control and measurement tools (camera, spatial light modulators, deformable mirror devices).

Also, this approach corresponds to the regular raster scan, in which the data is measured per pixel to form a complete data set.

Nevertheless, we note that for NV-based CS magnetic sensing, the discretization in frequency space is nearly arbitrary. While a completely continuous space is impossible and not practical computationally, there is **no physical (hardware) overhead to increasing the spectral resolution of the CS measurement basis**. This is in complete contradiction to the raster scan and sub-sampling approach, for which the discretization is directly (and linearly) related to the measurement time.

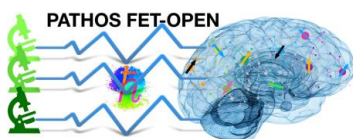
Thus, we can allow a fair comparison between CS and raster NV sensing, with an extremely high-resolution spectral basis space (limited by practical considerations and available computational power).

We note that this insight could have significant implications in a broad range of CS applications, clearly in fields such as NMR for which spectral CS is common, but also for optical scenarios, in which one can imagine dithering spatially the pixelized elements to achieve a nearly continuous sampling space.

3.2 CS experimental results

We compare the magnetic field error obtained in raster scan measurements vs. CS, as a function of the number of measurement points. This is performed in a confocal magnetic microscope, realizing magnetic field measurements with a spatial resolution of $0.3 \mu\text{m}$.

The baseline raster results are shown in Figure 3, with the measurement number corresponding to various sub-sampling parameters. The full spectral discretization basis chosen for these raster scans included 650 points (for a frequency span of 650 MHz).



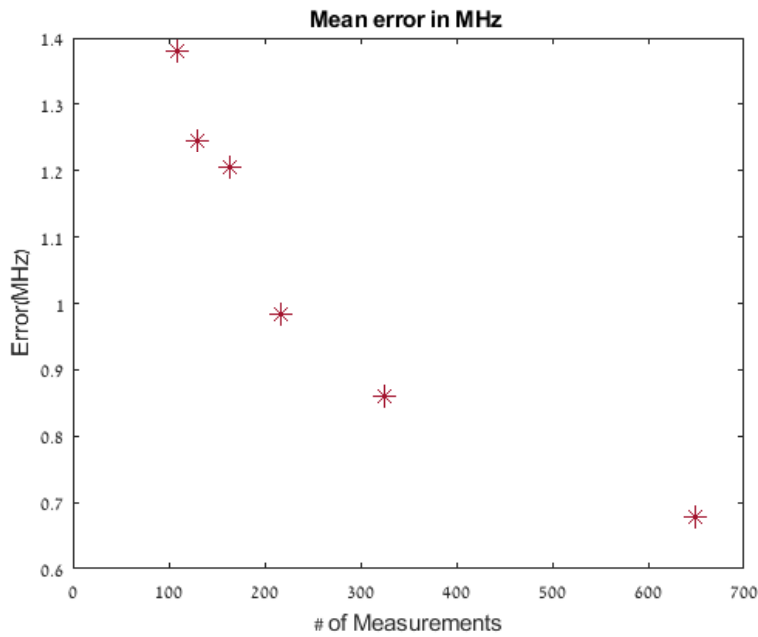


Figure 3: Measurement results of raster sub-sampling We plot the measurement uncertainty in MHz as a function of the number of measurements.

The CS results presented below plot the measurement uncertainty (mean error in units of MHz), along with the success probability of the algorithm, as a function of the number of measurements. Consecutive figures depict the results obtained using a growing density of points in the frequency basis (from 1200 in Fig. 4 up to 5000 in Fig. 7). We stress that this higher spectral resolution is achieved experimentally with no additional physical complexity (the microwave frequency source can reach an accuracy of nearly 10^{-6} Hz), and with a small computational complexity.

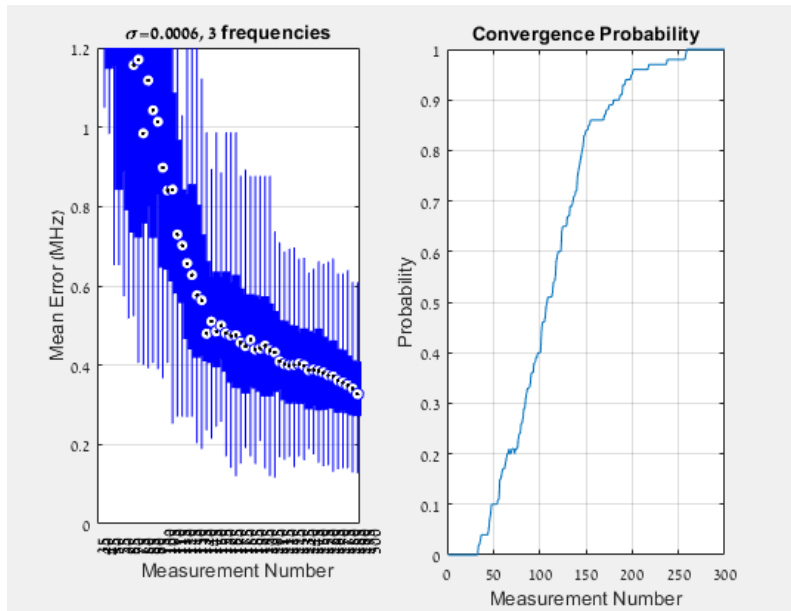
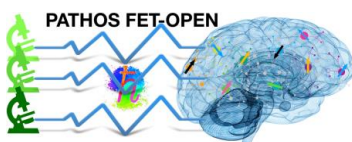


Figure 4: Advanced CS algorithm with 1200 spectral basis points.



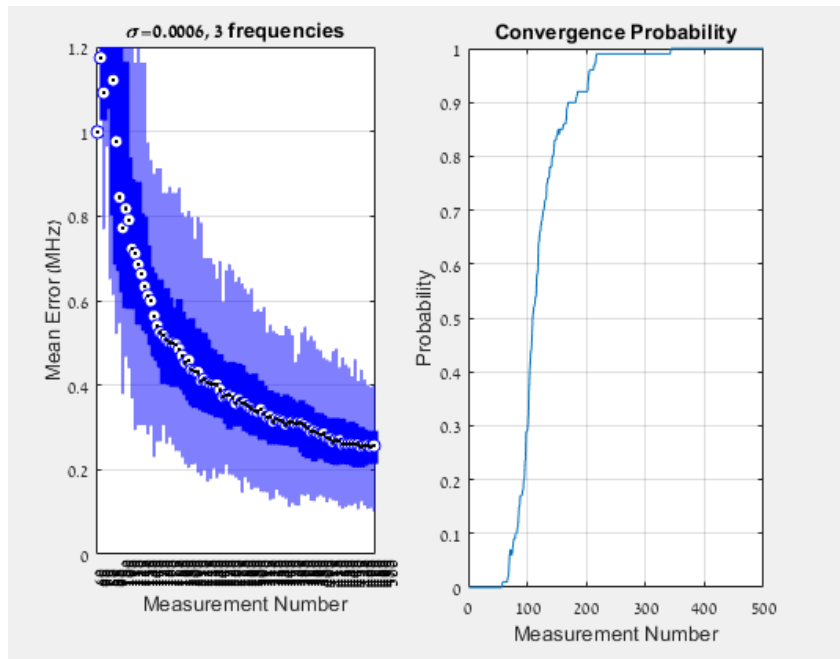


Figure 5: Advanced CS algorithm with 2000 spectral basis points.

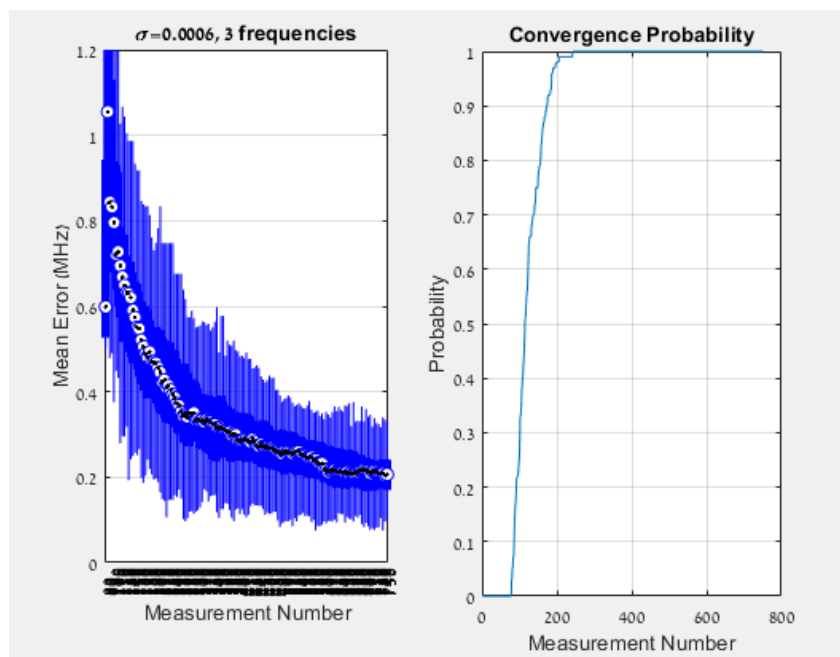


Figure 6: Advanced CS algorithm with 3000 spectral basis points.

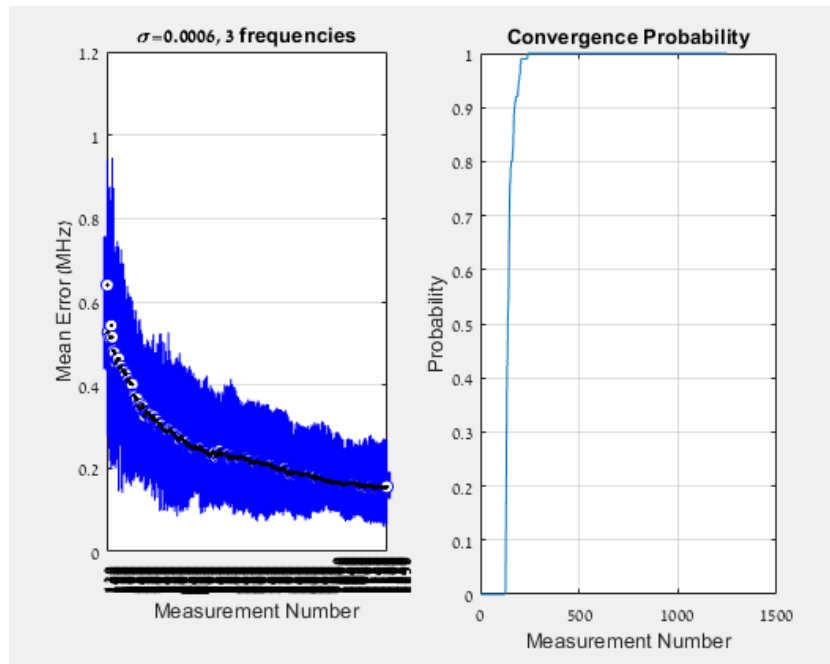


Figure 7: Advanced CS algorithm with 5000 spectral basis points.

4 Conclusions and future directions

The presented results indicate a significant step forward in CS-based sensing, and specifically in the context of NV-based high-resolution CS magnetic sensing.

Current results achieve nearly an order of magnitude improvement in magnetic field sensitivity compared to traditional CS (the standard approach described previously in D3.1), especially for high-bandwidth scenarios (small number of measurements). Compared to standard raster scanning and sub-sampling the improvement exceeds an order of magnitude.

We intend to finalize the experimental results and manuscript preparation and publish this research.

We intend to collaborate with the consortium members at UNIFI and Weizmann to further enhance our CS algorithms to incorporate techniques based in machine learning and feedback.

We expect that the novel approach presented here will have a broad impact beyond the field of NV sensing and could potentially significantly improve CS sensing in varying contexts.

