The need for speed: recovering undersampled MRI scans for glioma imaging.

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The diagnosis and management of patients with brain tumours such as glioma relies heavily on the use of MRI. Brain tumour patients typically undergo multiple MRI scans for diagnosis, surgical planning, and monitoring of chemo/radiotherapy. A typical neuro-oncology MRI protocol includes multiple pulse sequences (e.g. T1-weighted, T2-weighted, fluid-attenuated inversion recovery [FLAIR] and diffusion-weighted) before and after administration of contrast agents [1]. A full MRI examination typically requires between 30 and 45 minutes of scan time. The cumulative time associated with these scans over the entire patient journey is a burden not only to the patients, but also for the healthcare system at large, and contributes to delays in diagnosis and treatment. Strategies to reduce MRI examination time include elimination of contrast agents [2], reduction of the number of pulse sequences, as well as acceleration of image acquisition techniques – all of which may benefit from the use of artificial intelligence (AI).

The advent of multi-channel receiver coils provided the opportunity to decrease the time required to acquire MR images by undersampling K-space (the raw signal frequency domain from which the final MR images are reconstructed). So-called parallel imaging [3], compressed sensing [4], and related MR acquisition techniques allow for undersampling of K space with full non-aliased image recovery after computational unfolding [5]. With increasing acceleration factors, techniques such as compressed sensing become progressively ineffective and computationally demanding, to the extent that reconstruction times outweigh the actual image acquisition duration. Novel AI techniques are being successfully introduced by multiple MRI manufacturers to overcome this limitation and are not only surprisingly efficient timewise, but often also outperform conventional reconstruction algorithms by generating images with fewer artefacts and lower noise in a fraction of time [6].

In this issue of Lancet Oncology, a multi-institution collaboration led by the Heidelberg group [7] propose a hybrid AI-based technique that builds on previous work that developed model-based deep learning for inverse problems [8], allowing the incorporation of physics-based constraints to reconstruct high quality MR images from undersampled K-space data. They show that with acceleration factors up to 10 times (a factor of around four times more than achieved with commonly used conventional acceleration methods), there is negligible loss in clinically meaningful neuro-oncological outcome measures, such as (changes in) tumour volumes. Remarkably, the image reconstruction time of the vastly undersampled data was on the order of just seconds. The study made use of a large data set of local and multicentre scans of variable image quality and the results are thus likely to generalize well.

A potential limitation of the study [7] is that MRI scans were undersampled retrospectively, rather than using prospectively undersampled data using multi-receiver coils; however, in a

subset of subjects (without brain tumours), the quality of recovered images from multi-receiver coils was equally good, providing confidence that the method will perform well under real world conditions. Another potential limitation is the use of golden angle radial undersampling, which provides good reconstruction properties but is not commonly available for use in prospective acquisition for the range of image contrasts considered in this paper.

The findings from this study may have an impact well beyond glioma imaging, as the principles for image acceleration may apply to any type of MRI scan, each of which conventionally involves acquisition of redundancy-containing K-space data. Further extensions might include sharing of k-space information between the various pulse-sequences acquired within an imaging examination, to further capitalize on redundancies in image acquisition and further reduce overall examination times. In the near future, it is quite likely that total MRI examination times can be reduced to below 5 minutes, after which further reductions are unlikely to improve efficiency, given that total examination times are limited by getting patients in and out of the scanner. Alternatively, ultra-fast imaging methods may allow for additional information (e.g. arterial spin-labelling [ASL] for non-invasive perfusion mapping or chemical exchange saturation transfer [CEST] for cellularity) to be captured during the patient visit by exploiting image contrasts that are currently considered too expensive in time to justify inclusion in a diagnostic imaging session [9, 10].

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