Statistical Power or More Precise Insights into Neuro-Temporal Dynamics? Assessing the Benefits of Rapid Temporal Sampling in fMRI

Logan T. Dowdle[1,2,3†], Geoffrey Ghose[1,3], Kamil Ugurbil[1], Essa Yacoub[1*], Luca Vizioli[1,2†*]

[†] Corresponding authors

*Joint senior authorship

1. Center for Magnetic Resonance Research, University of Minnesota 2021 6th St SE, Minneapolis, MN 55455, United States
2. Department of Neurosurgery, University of Minnesota, 500 SE Harvard St, Minneapolis, MN 55455
3. Department of Neuroscience, University of Minnesota, 321 Church St SE, Minneapolis, MN 55455

Corresponding authors:

Logan T. Dowdle,
Research Associate,
Center for Magnetic Resonance Research,
University of Minnesota,
2021 6th Street SE,
55455, Minneapolis, MN
Email: logan.dowdle@gmail.com

Luca Vizioli,
Assistant Professor,
Center for Magnetic Resonance Research,
University of Minnesota,
2021 6th Street SE,
55455, Minneapolis, MN
Email: luca.vizioli1@gmail.com

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Abstract

Functional magnetic resonance imaging (fMRI), a non-invasive and widely used human neuroimaging method, is most known for its spatial precision. However, there is a growing interest in its temporal sensitivity. This is despite the temporal blurring of neuronal events by the blood oxygen level dependent (BOLD) signal, the peak of which lags neuronal firing by 4 to 6 seconds. Given this, the goal of this review is to answer a seemingly simple question – "What are the benefits of increased temporal sampling for fMRI?". To answer this, we have combined fMRI data collected at multiple temporal scales, from 323 to 1000 milliseconds, with a review of both historical and contemporary temporal literature. After a brief discussion of technological developments that have rekindled interest in temporal research, we next consider the potential statistical and methodological benefits. Most importantly, we explore how fast fMRI can uncover previously unobserved neuro-temporal dynamics – effects that are entirely missed when sampling at conventional 1 to 2 second rates. With the intrinsic link between space and time in fMRI, this temporal renaissance also delivers improvements in spatial precision. Far from producing only statistical gains, the array of benefits suggest that the continued temporal work is worth the effort.

Introduction

Functional MRI is one of the most common non-invasive brain imaging methods used to infer neuronal activity. By exploiting the coupling between neural responses and subsequent blood oxygenation changes (Logothetis et al., 2001), fMRI infers cortical activity by measuring local magnetic susceptibility changes via the Blood Oxygen Level Dependent (BOLD) signal (Ogawa et al., 1990). BOLD fMRI's popularity is likely owed to its ease of use, high contrast to noise ratio, and the relatively high spatial precision of its functional measurements, which ranks highest amongst non-invasive in-vivo neuroimaging techniques. In fact, with the growing availability of ultra-high field magnets (e.g. >= 7T) and the development of ever more efficient acquisition software and hardware, it is now routinely possible to acquire functional images with submillimeter spatial resolution (e.g. 0.8 mm isotropic; (Koopmans et al., 2010; Margalit et al., 2020; Olman et al., 2012; Siero et al., 2011), or even 0.5 mm isotropic; (Vizioli et al., 2020b)), allowing the investigation of some of the most fundamental units of neural computation, such as cortical layers and columns.

Despite the second to sub-second temporal resolutions with which we can acquire images with the BOLD fMRI technique, the vascular response lags neuronal events, blurring the temporal precision of neuronal responses. The temporal response of the BOLD signals follows a double gamma function, with a large signal increase peaking some 5 to 6 seconds after stimulation, and a less prominent undershoot far outlasting the positive peak with an overall duration of approximately 20 seconds (Glover, 1999). These numbers differ by many orders of magnitude in comparison to the occurrence of neural events, which span the millisecond range. Consequently, fMRI's temporal dimension has traditionally been neglected, with the vast majority of studies relying primarily on its spatial characteristics.

This is not to say that fMRI's temporal information has not been studied or used to interpret neural activity. For example, in considering relative temporal differences on how stimuli and task demands drive differential responses, there have been a number of investigations, including how delayed decision making

affects the BOLD signal (McGuire and Kable, 2015), investigations into the variability in temporal dynamics in the non-human primate auditory pathways (Baumann et al., 2010), or into the variability in the context of visual and semantic processing (Avossa et al., 2003; Formisano and Goebel, 2003; Vu et al., 2016).

Substantial research efforts have produced more efficient hardware and software, decreasing fMRI's repetition time (i.e. the time required to record a whole volume; TR). Recently, using these highly accelerated acquisition protocols, researchers have been able to acquire BOLD time series with unprecedented whole brain temporal resolutions (i.e. ~300-500 ms; (Lewis et al., 2016; Vu et al., 2016)). However, as most of what we know about the temporal characteristics of the BOLD signal have been learned with supra-second temporal resolutions, further work is required to integrate and fully appreciate the extent to which faster sampling allows more precise insights into neuro-temporal dynamics, more accurate characterization of the BOLD response function, or potential gains in statistical power compared to more conventional temporal resolutions. With faster TRs and improved signal to noise ratios (SNR) there is the exciting possibility of uncovering faster vascular dynamics, such as the initial dip.

In this work we aim to quantify the benefits of acquiring BOLD fMRI data with sub-second temporal resolutions. While the bulk of this work will focus on task-based fMRI, we will also touch upon the benefits of temporal resolution in the context of resting state fMRI, as resting state analyses are increasingly popular and widely used. We will review the literature and complement existing findings with empirical data to demonstrate the impact fast acquisitions have with regards to spatial and temporal information in fMRI. We will briefly touch upon the technical development that rendered ultra-fast fMRI possible. We will also examine the challenges associated with collecting, analyzing and interpreting fast data and consider the cost vs. benefit trade-offs of rapid data acquisition. Finally, as the BOLD signal in space and time are intrinsically linked and precision in one domain could inform or give rise to precision in the other, we will examine whether the ability to acquire higher temporal resolutions allows us to simultaneously and more precisely consider the information content from both dimensions.

Early temporal work.

Interest in fMRI began very early, shortly after its inception, and built upon the prior literature of *mental chronometry*, which primarily used reaction time measures to examine the timing of cognitive processes (Posner, 1978). Despite temporal lag and blurring, the goal for fMRI in this context is to determine the relative order of neuronal events within and across brain regions. While it is likely to remain unattainable to precisely identify the absolute ordering or directionality of neuronal events with fMRI, uncovering the *relative timing* of these events is more within reach. Historical examinations of the BOLD signal noted that events with an 8 second interstimulus interval (ISI) were visibly separate in signal traces (Bandettini et al., 1993). Another study (Kim et al., 1997) was able to resolve 2s long blocks of finger tapping tasks separated by only 3 seconds. These early proof-of-principle studies showed that the BOLD signal could be used to examine temporal dynamics, but such slow experimental designs were not optimized for widespread usage.

Following developments in statistical analyses and fMRI methods, work in mental chronometry grew more advanced. One method, used by Menon and colleagues, involves performing a linear fit to the initial rising portion of the hemodynamic response (HDR (Menon et al., 1998)). The point at which this best fit line intercepts the baseline BOLD signal is known as the time-to-onset (TTO). By comparing this onset time between regions, they uncovered latency differences between the primary visual cortex and the supplemental motor area in a visually cued motor task (Menon et al., 1998). Though the approach put forward by Menon et al. became a popular method for determining the relative timing of events, alternative approaches, such as fitting a single gamma function and deriving its onset (TTO) or the time-to-peak (TTP) (Miezin et al., 2000) have also been used. In general, these methods take advantage of the characteristic shape and relative consistency of the HDR in order to deconvolve sub-TR variability in neural timing. Studies like these, however, often implemented very specific task designs, which are not broadly applicable or used substantially less than whole brain coverage in order to reduce the TR.

Later work attempted to provide a more comprehensive view of BOLD temporal effects, using complex sequential tasks (combining auditory perception, mental imagery, and motor responses) to measure the order of mental operations across larger areas of the cortex (Formisano et al., 2002). Formisano et al. (2002) for example were able to detect sub-TR and sub-second delays between multiple regions despite TRs on the order of 2 seconds. These studies show that even with longer TRs, it is possible to extract rich temporal information from BOLD responses due to the consistent nature of the HDR. Of course, this consistency only emerges under specific circumstances, that is, within the same area, in response to the same or very similar stimulus. Another method to derive sub-TR timing effects that builds on this consistency combines the canonical HDR with its temporal derivative in a general linear model (GLM) framework. By comparing the amplitude of the temporal derivative to the canonical response, one can determine the relative timing of events (Henson et al., 2002; Liao et al., 2002). Building on temporally shifted HDRs, an alternative approach entails evaluating model fits between the fMRI time signal and HDRs with different time lags, simulating different timings of neuronal events. This approach has been argued to potentially lead to a temporal precision spanning the 200ms (Hernandez et al., 2002) or even 100ms (Bellgowan et al., 2003) range. In an alternative approach, Sigman and colleagues manipulated the relative timing and duration of a series of sequential events to jointly consider the magnitude and phase of the BOLD response in order to determine timing with 100ms precision (Sigman et al., 2007). By taking advantage of repetition suppression effects, Ogawa and colleagues showed that fMRI could even detect modulations in the 10s of milliseconds differences when considering cross hemispheric inhibition or neural refractory processes due to short interstimulus intervals (Ogawa et al., 2000).

These studies highlight early interest in fMRI temporal dimension. However, in spite of these dramatic temporal findings, early reports present a number of limitations. These approaches are in fact limited in scope, as they are only applicable to a small subset of possible scientific contexts and questions. This limitation is related to a number of factors, including the necessarily constrained or highly specific experimental designs, the typically large voxel sizes, or very limited fields of view. As such, a clear need emerged for methods that

allowed for faster sampling in conjunction with whole brain acquisition or, alternatively, a limited field of view with substantially higher spatial resolution.

Advancements in MRI

To date, most of the fMRI applications looking to exploit temporal information did not have the benefits of fast or sub-second temporal sampling combined with relatively high SNR/CNR and large, or even whole, brain coverage. In recent years there have been substantial improvements in magnet hardware, including an increasing prevalence of ultrahigh field (>= 7 Tesla) strengths and improvements in transmit and receive coil arrays. The use of higher magnetic fields results in improved image SNR as well as increases in the CNR of the BOLD fMRI signal. These gains can be traded in for increased spatial resolution (as has historically been the case), increased temporal resolution, or some combination of both. The development in coil array technology has permitted the spatial encoding of signals via the sensitivity profile of the individual coils, with higher channel count coils allowing for more precise spatial encoding. Spatial encoding using information from the RF coil arrays means less required spatial encoding from MRI gradient coils or ultimately the feasibility of accelerating conventional image acquisitions which rely on gradient encoding alone. Multi-channel array coils can be used to spatially encode information during the encoding of a single slice, which primarily facilitates the acquisition of higher spatial resolutions, or used to encode multiple slices simultaneously, which can significantly improve the temporal resolution of the acquisition.

Simultaneous multi-slice (SMS) or multiband (MB) imaging (Feinberg et al., 2010; Moeller et al., 2010) was introduced to reduce the total time needed to acquire a volume by collecting multiple slices simultaneously. This led to a revolution in the fMRI field for multiple reasons. While introduced to improve the temporal resolution or efficiency, this did not mean that it was only relevant to high temporal resolution applications. On the contrary, since higher spatial resolution studies were inherently temporally inefficient due to the many more slices required, the introduction of MB/SMS actually made higher spatial resolution studies

feasible via much more tolerable TRs or allowing for increased coverage in field of view limited studies. The method is, of course, equally amenable to improving the temporal sampling for a given spatial resolution and coverage. By maintaining a constant resolution and coverage, entire volumes can be acquired in a fraction of the time – up to 6 or even 10 times faster, as was demonstrated by the Human Connectome Project (Uğurbil et al., 2013). Alternatively, MB has been exploited by auditory researchers to allow more "dead time" between TRs, enabling longer stimulus presentation time in the absence of hardware related acoustical noise (De Martino et al., 2015). With typical 3T fMRI voxel resolutions (i.e. 2-3mm isotropic), it is possible to get whole brain images in less than a second or even under 500ms. Novel acceleration methods continue to be developed, pushing acquisition times for reasonable brain volumes well below 500 or 100 ms (Chang et al., 2013; Lin et al., 2011; Vu et al., 2018) Collectively, the increase in receiver coil elements, improved accelerated acquisition and reconstruction methods (Koopmans and Pfaffenrot, 2021), and higher field strengths, all provide an encouraging outlook for rapid temporal sampling in fMRI. However, as temporal resolution becomes finer, appropriate analytical strategies to deal with these super-fast acquisitions are required.

Statistical and Methodological Considerations

Hemodynamic Response Variability

The conventional HDR has served the fMRI community well and, through parametric manipulations and analyses strategies, it is possible to determine sub-TR shifts, even with relatively low temporal resolution. However, the shortcomings of the canonical HDR, derived from sensorimotor and auditory cortices at 1.5 Tesla with 2.2x2.2x5 mm^3 voxels (Glover, 1999), are becoming increasingly clear. It has long been known that the HDR can vary depending on the duration of the stimulus (Boynton et al., 1996; Glover, 1999), the precise stimulus presented (Boynton et al., 1996; Thompson et al., 2014) , and the specific region studied (Gonzalez-Castillo et al., 2012; Handwerker et al., 2004; Taylor et al., 2018). Statistical approaches, such as adding more

basis functions to the conventional HRF to account for temporal shifts and dispersion (Pernet, 2014) have improved, but not eliminated, the impact of hemodynamic variability at typical sampling rates. Rapid sampling can also mitigate these effects, allowing the HDR to be better characterized (Lewis et al., 2018; Lin et al., 2018, 2013). Unbiased estimates of the HDR can also uncover elusive temporal features, such as the initial dip (Buxton, 2001), which is absent from canonical HDR models.

In modeling the HDR with insufficiently flexible basis functions, or inadequate temporal resolution, temporal differences can instead manifest as differences in amplitude, which can lead to incorrect inferences (Lindquist et al., 2009). This challenge increases as briefer stimuli (i.e. less than 1 second) are used. When stimuli are 1 second or longer, the BOLD response tends to add linearly, such that a response to a 2 second stimulus matches the summation of a pair of 1 second stimuli (Boynton et al., 2012, 1996). With rapid sampling and brief stimuli, the hemodynamic model requires further consideration and models may need to be updated to account for these differences. A discussion of the precise shape of the HDR under all possible stimulus types, durations and sampling regimes is beyond the scope of this paper (see Polimeni & Lewis in the current issue for further consideration of these points (Polimeni, and Lewis, 2021)).

A potential pitfall for any indirect measure such as fMRI, is the inability to differentiate between vascular and neuronal temporal dynamics. In other words, there is the danger of interpreting vascular delays as meaningful temporal differences in neuronal responses. For example, findings that longer time-to-peak is correlated with larger FWHM responses appear to uncover venous effects (de Zwart et al., 2005). That is, hemodynamic signaling delays and blood transit time lead to larger and sluggish responses from venous drainage. As such, extracting neuronally relevant temporal information from BOLD fMRI data is not straightforward.

Statistical implications of faster TRs in fMRI

Shorter TRs can extract timing information of cognitive processes (such as face processing (Gentile et al., 2017) and can lead to more precise parameter estimates, higher tSNR, and larger t-statistics (Chen et al., 2015; McDowell and Carmichael, 2019; Posse et al., 2012), which can be loosely defined as the estimated amplitude of the BOLD response (or contrast) divided by the model's standard error. Other works find more modest effects, with limited benefits due to faster sampling (Bhandari et al., 2020; Demetriou et al., 2018). These mixed results may suggest that faster sampling combined with typical analysis methods are unlikely to give large benefits, however this should not be a cause for concern. The primary issue at hand is that most comparisons between conventional BOLD fMRI and faster sampling MB based BOLD fMRI have not considered an exhaustive comparison of how the removal of structured noise (discussed below), could improve results. In addition, these papers use the canonical HDR rather than customizing the response for each participant, task or voxel. Finally, these papers consider, by and large, typical analyses strategies examining groups of subjects. While these analysis strategies are valid and widely used, they may miss or average out the effects that are most interest to rapid fMRI researchers. Unsurprisingly, the benefits of faster sampling may require additional processing steps or special considerations to fully gain the benefits or appropriately handle the corresponding tradeoffs.

The increase in temporal samples is the most obvious benefit of faster sampling, which is typically equated with a one-to-one increase in degrees of freedom. However, individual volumes of fMRI data are not statistically independent, and instead exhibit e a strong temporal autocorrelation, which must be accounted for in order to produce valid inferences (Bullmore et al., 1996) when using the typical t-statistic/p-value approach. Failure to do so will result in an artificial inflation of statistical power, especially for GLM related contrasts and associated p-values. In conventional fMRI, this problem is often addressed using relatively simple autoregressive models (i.e. AR(1)) (Friston et al., 2002), which attempt to estimate the amount of autocorrelation in the timeseries using only one preceding timepoint. While this appears to be valid for 2 to 3

second sampling rates, it is inadequate for second to sub-second TRs, leading to inflated t-statistics (see Figure 1D) and concerns about false positives (Bollmann et al., 2018; Chen et al., 2019; Lenoski et al., 2008; Olszowy et al., 2019; Purdon and Weisskoff, 1998). On the other hand, beta values, reflecting BOLD response amplitude, are minimally changed by accounting for temporal autocorrelations (see Figure 1C). As sampling rates increase, the relative contribution of thermal noise increases (due to lower SNR from shorter TRs) and autocorrelation effects span more volumes (Chen et al., 2019). Modeling physiological noise using methods such as RETROICOR (Glover et al., 2000; Olszowy et al., 2019), can lead to whiter residuals, however it does not fully solve the autocorrelation issue (Bollmann et al., 2018), so these more advanced methods are still required.

In dealing with autocorrelation correction, estimating parameters on a voxel by voxel or tissue by tissue basis is preferred for accuracy (Eklund, Anders et al., 2012; Lenoski et al., 2008) This is due to variability in the amount of temporal autocorrelation across the brain (Kaneoke et al., 2012), particularly between grey and white matter (Worsley et al., 2002). While the basic AR(1) is insufficient, there is not a clear answer as to what model order is required. AFNI uses a voxel-wise autoregressive moving average (ARMA(1,1)) (Chen et al., 2012), which combines the AR(1) model with a moving average (MA(1)) component to account for the presence of thermal noise in the fMRI timeseries. This relatively simple addition appears to perform well, even at sampling rates as low as 645 milliseconds (Olszowy et al., 2019), though there is potential for improvement. In contrast to the default AR(1) model, SPM has recently implemented a method called FAST, which uses a collection of exponentially decaying functions and their derivatives to fit the timeseries autocorrelation, which also successfully reduces false positives (Corbin et al., 2018; Olszowy et al., 2019). Fitting complex AR models for each voxel does raise statistical as well as computational concerns. While higher AR models (i.e. considering more time lags) can be used to effectively account for autocorrelation, estimating higher and higher model orders is computationally inefficient and may result in overfitting, leading to spurious estimates (Bollmann et al., 2018). A recently developed approach nicely handles both the voxel-by-voxel fitting and

excessive model order concerns by using methods based in information theory to select the autoregressive model order, rather than using a modification of the AR(1) approach (Luo et al., 2020). Tested against resting state data with 300 and 500ms TRs as well as simulated data they show that this method successfully controls false positives, though model orders as high as AR(10) may be required.

Collectively these findings show that, as sampling rates increase, the field should consider autocorrelation approaches that estimate use higher model orders and perform estimates on a voxel-by-voxel basis. These concerns, which primarily relate to conventional GLM-based approaches for statistical inference, apply not only to fast TR data, but to fMRI in general, and become more apparent in extreme cases, such as that of ultra-fast fMRI.

One frequent approach, equally applicable to standard and fast fMRI, that effectively circumvents the above considerations related to the inflation of statistical power, is the implementation of independent 2nd order inferential statistical tests. These can be carried out across subjects, but also within subjects, across, for example, single runs estimates of BOLD responses. Univariate (e.g. (Dowdle et al., 2021)) and multivariate (e.g. (Kriegeskorte and Bandettini, 2007; Vizioli et al., 2020a)) parametric tests using subjects or runs as independent observations are in fact routinely used. Nonparametric statistical approaches, such as bootstrap confidence interval that make fewer assumptions about the data distribution, thus avoiding many of these concerns, are also a valid alternative. In other words, the concerns about inflation of statistical power with ultra-fast fMRI are primarily rooted in GLM-based statistical inferences. These concerns can be mitigated by assigning statistical significance on the basis of empirical p-values that are derived from independent estimates of BOLD activation, such as different subjects or experimental runs, rather than using GLM contrast-based p-values.

In summary, fMRI's increased temporal resolution, which allows a better characterization of BOLD responses, also leads to a significant increase in the number of temporal samples, introducing an additional degree of complexity in analyzing and interpreting ultra-fast data. However, there are a number of more or

less refined strategies to deal with these additional complexities, that can also be circumvented using non GLM-based inferential statistic, allowing exploitation of fast-TR data.

Empirical effects of faster sampling rates.

Though a number of questions remain about the best methods to use and how acquisition strategies will alter metrics such as tSNR, some of these effects can be readily demonstrated. Here we show evidence of these statistical considerations with a dataset collected at 7T, using visual stimuli consisting of faces at varying phase coherence levels.

Four (2 female) healthy right-handed subjects (age range: 18-31) participated in the study. All subjects had normal, or corrected vision and provided written informed consent. The local IRB at the University of Minnesota approved the experiments. In the scanner, participants were instructed to perform 2 tasks: face detection and fixation. In the former, we varied the phase coherence of the face stimulus from 0% to 40% coherence (10% step size) and participants were instructed to respond as quickly as possible by pressing one of 2 buttons on a button box to indicate whether they perceived a face. In the latter, participants were instructed to press one of the 2 buttons on the button box when the fixation color changed to red. Every 500 ms, the fixation changed to one of five colors (red, blue, green, yellow or cyan) in a pseudorandom fashion, avoiding consecutive presentations of the same color. The frequency of button presses was kept constant across tasks. Visual stimuli were identical across tasks in order to examine differences based only on attentional effects. Tasks were blocked by run and counterbalanced across participants.

We acquired 3 runs per task. Each run lasted approximately 3 mins and 22 secs and began and ended with a 12-second fixation period. Within each run, we showed 40 images (5 phase coherence levels x 4 identities x 2 genders) presented for 2000 ms, with a 2000 ms interstimulus interval (ISI). Importantly, we introduced 10% blank trials (i.e., 4000 ms of fixation period) randomly interspersed amongst the 40 images, effectively jittering the ISI.

All functional MRI data were collected with a 7T Siemens Magnetom System using a 1 by 32-channel NOVA head coil. BOLD fMRI data were collected using 4 unique sequences varying in TR from 1000 to 323ms (Table 1). For each sequence, parameters were adjusted, including spatial resolution, in order to produce images with comparable signal to noise ratios (SNR) despite changes in TR. The flip angle was chosen to match the Ernst angle independently for participant and sequence. The dataset with a 1s TR dataset was used to create the visual cortex regions of interest used in the following sections, using the contrast to non-zero faces, and adjusting the threshold until voxels that were in early visual cortex were isolated. These maps were then resampled for the more rapid acquisitions.

TR (ms)	Multiband	In-Plane Acceleration (GRAPPA)	Partial Fourier	Spatial Resolution (mm)	TE (ms)	Bandwidth (Hz)	Number of Slices
1000	5	2	7/8ths	1.6x1.6x1.6	22.0	1923	85
590	5	2	7/8ths	2.0x2.0x2.0	15.6	2170	70
414	5	2	7/8ths	2.5x2.5x2.5	16.4	2193	55
323	5	2	7/8ths	3.0x3.0x3.0	14.2	2231	45

Table 1. Sequence parameters used for the empirical demonstration data. TR: Repetition Time; TE: Echo Time.

We processed the data in AFNI, performing slice time, motion and distortion correction and automated alignment to each participant's anatomical image. Example images from each TR are shown in Figure 1, panel A. The images are similar, with the primary visible difference due to the voxel size. In order to confirm that the chosen sequence parameters successfully produced images with comparable SNR despite the changes in spatial and temporal resolutions, following (Dietrich et al., 2007), we calculated an image SNR metric by dividing the mean signal intensity in the gray matter by the standard deviation of the background (i.e. "noise") signal. Gray matter was defined using a mask of the cortical ribbon derived from FreeSurfer (Fischl and Dale, 2000) and resampled for the varying spatial dimensions of each of the acquisitions. Background signal was taken as the standard deviation within a sphere of 9mm radius, positioned outside of the head and regions of

ghosting. Consistent with visual inspection, this estimate of image SNR did not meaningfully differ across temporal resolutions (Figure 1 A).

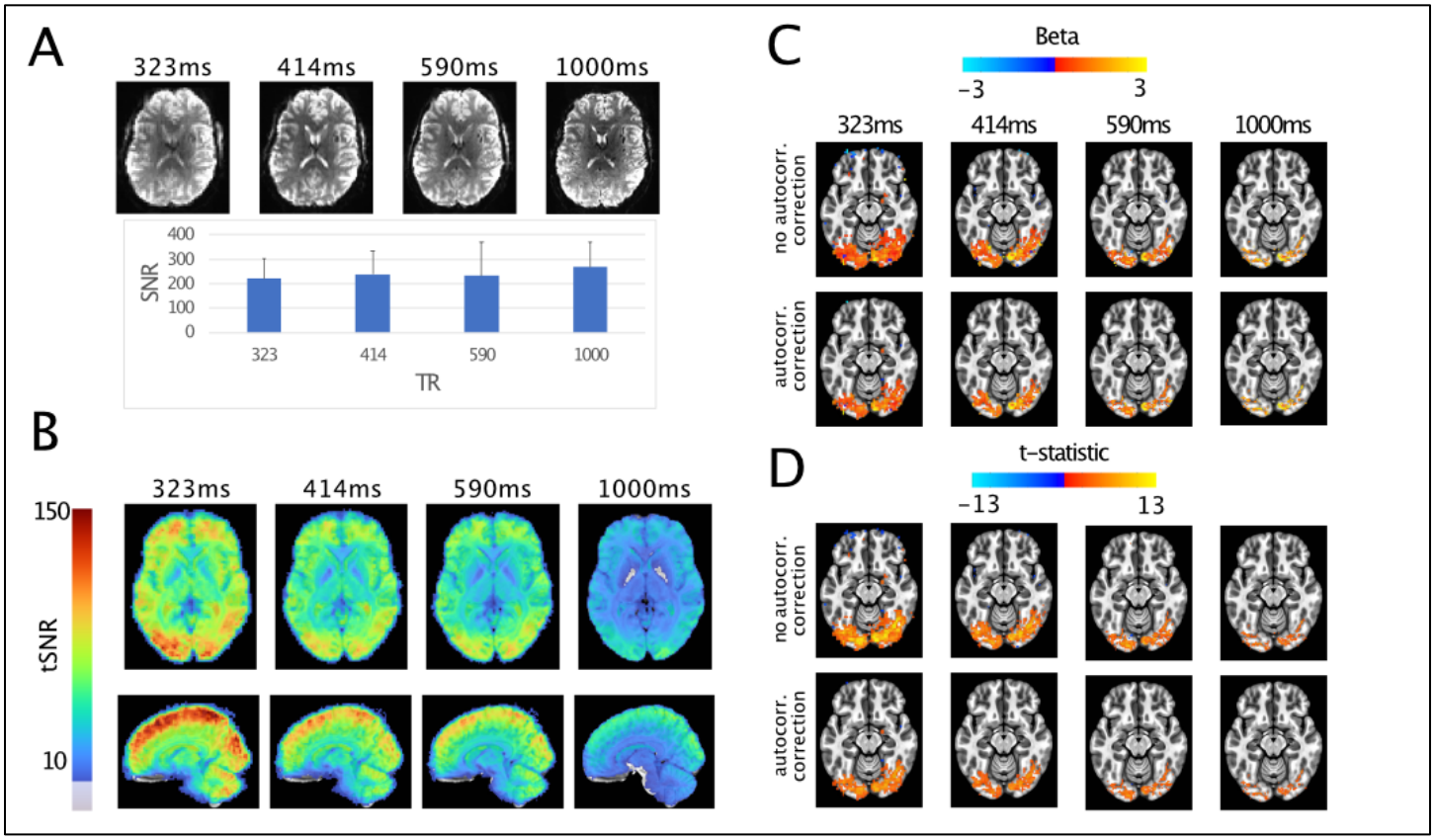

Figure 1. Effects of faster sampling on statistical and signal characteristics. A) Image SNR characteristics, with images from a single subject. No differences in image SNR are observed. **B)** tSNR measures, average over subjects. Faster sampling leads to substantial gains in tSNR throughout the brain, with the largest effects visible with a sampling rate of 323ms. **C)** Activation amplitudes (betas) for the nonzero phase face stimuli compared to baseline. Betas are little changed due to accounting for autocorrelation in the timeseries. **D)** T-statistics for the same contrast. Unlike betas, both the extent and the magnitude of the t-statistics is reduced when we attempt to account for temporal autocorrelation. These effects are most pronounced for the 323ms data. For visualization purposes, the beta and t-statistic maps use a t threshold of $p<0.01$ from the average t-statistics.

Next, we computed the voxel-wise acquisition specific TSNR, defined as the mean of the signal in each run, after detrending with polynomials up to order 3, divided by the standard deviation. tSNR maps were

warped into standard space independently for each sampling rate and averaged (Figure 1B). In contrast to image SNR, the tSNR shows increases as faster sampling is used. The highest tSNR is found for the most rapid acquisition and particularly in cortical areas. This is likely due to a number of factors, including reduced aliasing of physiological noise, better estimates of motion, and better sampling of the HDR. It should be noted though that, in light of the concomitant changes in temporal sampling rates and spatial resolutions across sequences, the observed tSNR gains could be due, in part, to the larger voxel sizes, which increase as TRs get shorter. While the larger voxels do likely contribute to the higher tSNR measures, the imaging parameters were chosen to match image SNR (as supported by the SNR estimates shown in Figure 1A), suggesting that at least part of the observed improvements are related to faster sampling.

In order to examine the statistical properties of the data, each run was scaled to have a mean of 100 and we then performed a GLM using the canonical HDR as implemented in AFNI ('SPMG1'). The resulting beta and t-statistic maps were then warped into standard space and averaged for visualization purposes. Figure 1 panel C shows the mean beta values (only voxels with average t-statistic corresponding to $p>0.01$ are shown) from the contrast of all nonzero phase face stimuli versus baseline, conducted without (top) and with autocorrelation correction (bottom). Consistent with expectations, beta values show minimal differences between these two approaches, however, large differences are seen between different repetition times. In the 1000ms acquisition, the activation patterns show fine scale detail and larger amplitudes relative to the faster TRs, which also used larger voxel sizes, leading to partial volume effects. Though there is a loss of spatial precision due to the design of this experiment, there are benefits of rapid temporal sampling which will be discussed in further detail in a subsequent section.

In contrast to the lack of differences between betas, Figure 1, panel D shows the t-statistics maps from the two respective models. While a TR of 1000ms has very similar t-statistics between the two different approaches, larger differences are seen for the faster TRs. Two directly related effects are observed. First, the activation extent is reduced, as fewer voxels survive the arbitrary $p>0.01$ threshold. Second, the magnitude of

the t-statistic is reduced, particularly in the case of the 323ms dataset, when autocorrelation correction is used. The peak magnitude of the t-statistics are reduced as the autocorrelation correction reduces the inflated t-statistics.

Collectively these results highlight how, in an acquisition strategy where image SNR is matched across different protocols, temporal SNR can still increase with faster sampling rates and, additionally, reasonable patterns of activation can be generated for each acquisition. These findings also show the wide range of spatial-temporal scales available to investigators. One could also imagine reducing the coverage in order to achieve comparable temporal resolutions for a given spatial resolution.

Denoising approaches can benefit from faster sampling

Physiological noise arises primarily from the oscillatory nature of respiration and cardiac pulsations, which are typically around ~0.3 and ~1 Hz, respectively (Chen et al., 2019). While traditional fMRI sometimes samples fast enough to capture respiration (TR of ~1.5s), cardiac signals require substantially faster (<500 msec) acquisitions. Under the slow TR fMRI framework these signals do not disappear, but are instead aliased into lower frequencies, corrupting the portion of the spectrum in which task responses or resting state fluctuations appear. With sufficiently fast sampling rates, it is often believed that it is possible to remove the unaliased physiological signals via filtering, however, this ignores higher order harmonics (Chen et al., 2019). Encouragingly, modeling methods that use cardiac and respiratory recordings can be used (Glover et al., 2000; Kasper et al., 2017) to generate regressors that capture and remove physiological noise. A limitation of this approach is that researchers often do not collect physiological recordings or are unable to acquire sufficiently clean recordings. Of course, if the physiological signals are corrupting the data, perhaps it is possible to derive the waveforms in a data driven manner. This idea was present in the early days of fMRI, with work using the phase information present at the center of k-space (‘frequency’ space, i.e. the Fourier transform of the image) to estimate respiratory and cardiac signals (Le and Hu, 1996). Recent work has conceptually built on this

approach, reconstructing these physiological signals in a data driven manner when TRs are sufficiently short. Using an approach labeled HRAN, a statistical model of harmonic regression with autoregressive noise, Agrawal and colleagues show that with fast enough sampling, estimates of cardiac and respiratory noise can be produced from the fMRI data alone (Agrawal et al., 2020). These estimates performed as well as physiological noise regressors from RETROICOR and did not require separate physiological noise recordings.

Another approach involves examining time lagged correlations of the cardiac trace, as measured from pulse oximetry, in order to map its time lag across the brain (Tong et al., 2014). When sampling is sufficiently fast, it can be seen that the cardiac signal has effects across the whole brain, though the timing varies – an observation that requires rapid sampling to examine. This method can also be used to examine the low frequency fluctuations that are present in fMRI data, and again requires rapid sampling to reduce the aliasing of cardiac and respiratory signals into the lower frequencies of interest (Hocke et al., 2016). Though some harmonics may remain aliased even at fast sampling rates, there is a clear benefit of faster sampling in uncovering and potentially removing these confounding effects. At a minimum, fast sampling reduces the amount to which high frequency physiological noise components are aliased into the lower frequencies which are typically of interest for fMRI.

In addition, structured noise (which include noise from sources such as bulk motion) removal processes do appear to benefit from shorter TRs. With fast sampling, independent component analysis (ICA) methods appear to have more success in removing physiological noise and motion (Boubela et al., 2014; Griffanti et al., 2014), which can be applied in both task and resting state analyses. Multi-echo fMRI, a method that captures multiple “exposures” of the BOLD contrast in a single volume acquisition, can be combined with ICA methods for denoising (Kundu et al., 2012). With multi-echo fMRI contrast, denoising can be done based on whether there is a dependence of the signal on the echo time and then classifying signals as either BOLD or noise-like effects (Kundu et al., 2017, 2012). Multi-echo denoising used with ICA can also benefit from faster sampling rates (Boyacioğlu et al., 2015; Olafsson et al., 2015). Other denoising methods, such as GLMDenoise (Kay et al.,

2013), which uses cross validation across multiple runs and derives noise regressors using principle component analysis (PCA) after determining a subject specific HDR, is also expected to perform better with faster sampling. Broadly speaking, any method which attempts to partition out insufficiently sampled temporal components of the signal is expected to benefit from faster sampling.

In addition to structured noise sources as discussed above, thermal noise is also a concern in fMRI. Thermal or system noise is Gaussian in nature and its relative contribution to the image increases with finer spatial sampling (Triantafyllou et al., 2011, 2005) or with the use of accelerated techniques (Todd et al., 2017). In rapid temporal sampling, the ratio of signal to thermal noise is also decreased. Unlike physiological noise sources, which are more detectable with faster sampling, there is no such benefit for thermal noise. Retrospectively, the thermal noise contribution in fMRI has typically been suppressed using spatial smoothing, which necessarily reduces spatial precision and can erroneously shift peak activation (Geissler et al., 2005; Jo et al., 2008; White et al., 2001). In high-speed fMRI, this may be even less desirable, as spatial resolution sacrifices have already been made to achieve the desired temporal resolution. Recent developments have led to methods that use low-rank patch based PCA methods to remove, in part, noise that cannot be distinguished from Gaussian (i.e. thermal noise) in the fMRI timeseries (Vizioli et al., 2020b). This method, known as NORDIC, can lead to increased t-statistics without the image blurring that is associated with spatial smoothing (Vizioli et al., 2020b).

Here we show, using the previously introduce 323 millisecond dataset, that the NORDIC method is able to suppress thermal noise in rapidly sampled data. The NORDIC method was applied to these data before any processing. Subsequently, identical processing methods were applied to the images (see Empirical effects of faster sampling). This led to substantially less variance in the timeseries, and additionally, following the suppression of thermal noise, the contribution of physiological noise sources is clearer (Figure 2). The top left shows this for a single subject single voxel case in which the reduction of noise in the timeseries is clear, while the overall structure remains intact. This effect is apparent in the frequency domain after a fast Fourier

transform (FFT), in which the respiratory (at ~0.3Hz) and cardiac (~1Hz) frequency peaks can be clearly distinguished after NORDIC, but are buried in the high levels of thermal noise in the original data. These effects are also clear in the data after meaning over 419 voxels in the visual cortex ROI. While the mean timeseries are nearly identical, the FFT plot shows a clear reduction in power across a broad band of frequencies. As faster sampling become the norm, there is a clear need for methods that are able to suppress the relatively larger contribution of thermal noise. This is particularly true for the higher signal frequencies that are of interest and often contain physiological information that may be difficult to resolve due to thermal noise.

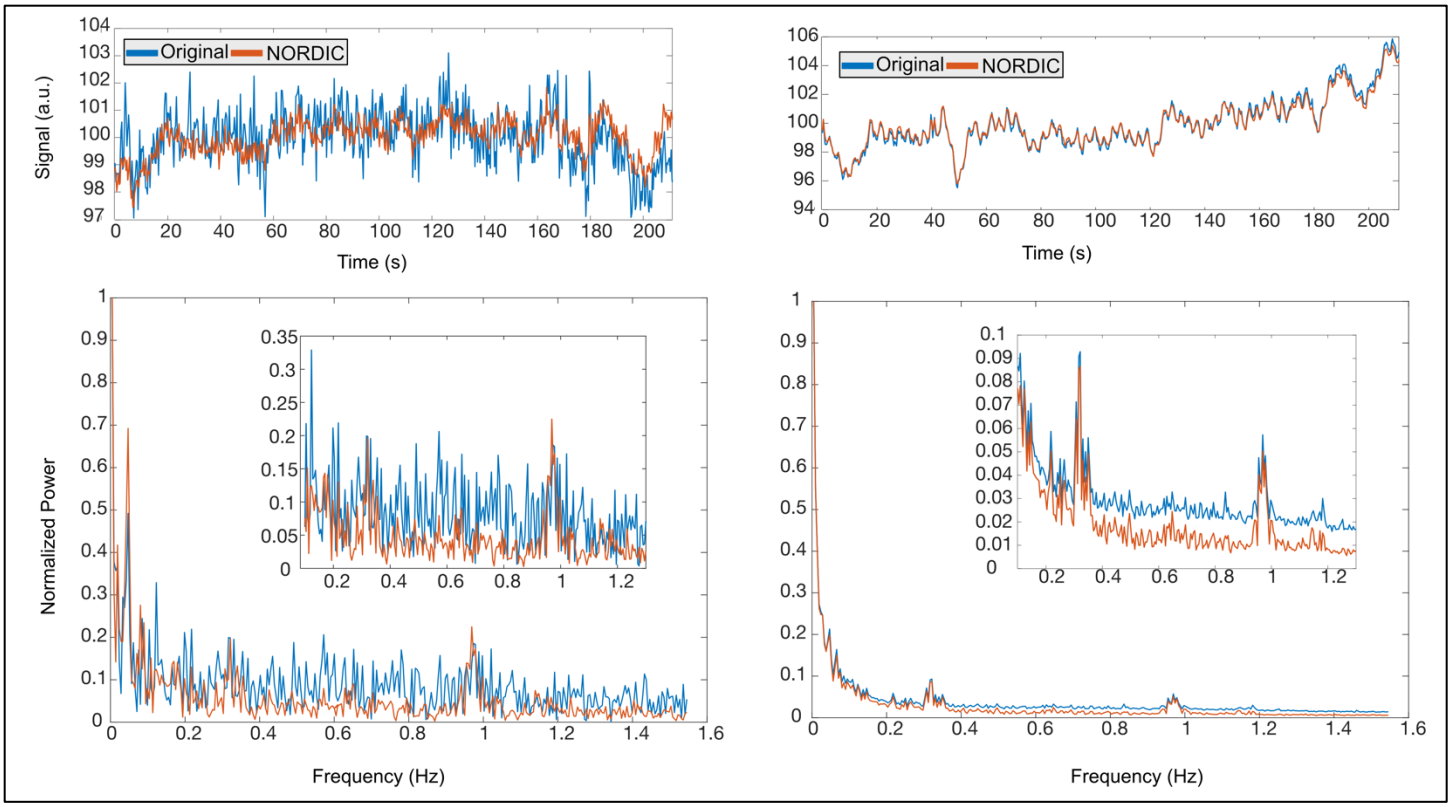

Figure 2. Timeseries and FFT plots show effects of NORDIC processing for 323ms data. Top Left. The timeseries for a single voxel is shown for the original (blue) and NORDIC-processed (Orange) data. The original data shows a larger amount of spurious noise, which is suppressed following NORDIC processing. **Bottom Left.** The FFT plots for this single voxel show that the effects of NORDIC are present across the entire power spectrum, though the respiratory and cardiac peaks at 0.3Hz and 1Hz remain in the data and are more easily seen. **Top Right**. Using the mean within the 419 voxels of the visual cortex ROI, there is little difference in the timeseries before and after

NORDIC processing. **Bottom Right**. The FFT plot again shows a large suppression of noise, with physiological noise sources left intact.

Collectively, these findings show that there is a synergistic effect of faster sampling and denoising. These methods, whether they are tuned to remove physiological noise, other structured noise, or even thermal noise, appear to benefit from the increased dimensionality and reduced temporal aliasing achieved with fast fMRI acquisitions. This in turn produces better estimates of the hemodynamic response, higher t-statistics, and/or better parameter estimates. More work is required to sufficiently tease apart the benefits and downsides of faster imaging, as it is plausible that optimal analyses strategies will lead to more substantial analytical gains that have yet to be realized using methods that were developed for much slower sampling rates.

Sampling rate interactions with common preprocessing steps

Estimating and correcting for motion is a critical step in the fMRI analysis pipeline. Faster sampling can allow for a more precise snapshot of motion, depending on the time scale of the motion relative to the TR. Volumes are aligned to one another, typically using a least-squares rigid body approach (i.e., 6 degrees of freedom), which reduces but does not entirely remove the effects of movement. Faster imaging could lead to more accurate motion estimates since motion might be captured instead of aliased, producing better outcomes after motion correction. However, there is a concern in that motion parameters in fast sampling regimes suggest that participants are constantly moving, with previously unnoticed motion occurring in the phase-encode direction of the EPI scan (Power et al., 2019). These effects have been studied, finding that they are due to a number of factors (Fair et al., 2020; Power et al., 2019). Namely, respiration is driving motion effects that are both “real”, in that the head is moving due to breathing, as well as apparent motion of the head resulting from magnetic field shifts due to movement of the chest during breathing (Power et al., 2019).

In order to appropriately correct for motion, it may be necessary to notch filter the motion estimates in the respiratory band (Fair et al., 2020).

One other consideration is the impact of the slice timing correction. In typical 2D acquisitions, each slice (or slice group for multiband) is acquired at a unique point in time, however, the entire volume is considered a single timepoint by default. Particularly in event related studies (Sladky et al., 2011) correcting for within volume differences in timing improves accuracy and can be critical. The process of doing this does incur some penalty due to the necessity of interpolating the unmeasured timepoints and recent work has shown that slice-timing prior to motion correction can yield incorrect motion estimates, reducing the magnitude of sudden movement in particular (Power et al., 2017). With faster temporal sampling, the need for slice timing corrections, and thus interpolation, is reduced (Sahib et al., 2016; Sladky et al., 2011) or even eliminated.

Neural Dynamics

Relationship between sampling and task effects

Faster sampling can also improve task separation. While amplitude has long been used as the key separator for task activation within the GLM framework, two slightly shifted HDRs can have identical amplitudes, despite very different response profiles (Lindquist et al., 2009).

Unbiased deconvolution models, such as those using finite impulse response (FIR) approaches, which directly estimate the HDR, have allowed for detailed investigations into the temporal dynamics of the BOLD signal. Under the FIR framework, a researcher selects a temporal window, or the number of TRs they expect the stimulus response to last, in which to estimate effects. The design matrix for the GLM then consists of a series of delta functions corresponding to the length of the time window multiplied by the number of unique stimulus conditions. This flexible and unbiased (i.e., no assumption of shape is made) approach produces a series of betas for each stimulus condition after the GLM, corresponding to the temporal estimates of the

HDR. This approach can be used to deconvolve stimulus responses without making assumptions about specific shapes (Glover, 1999; Lewis et al., 2018). While FIR computations avoid mismodeling and mistaking temporal differences as amplitude effects, they do have the potential to overfit noise (Lindquist et al., 2009). Thus, their usage requires careful consideration of data quality and the chosen temporal window.

Empirical demonstration of the benefit of faster sampling: 1. Identifying task differences over time

To demonstrate the benefit of rapid temporal sampling within the FIR framework, which can be used to uncover differences between tasks that may be overlooked with slower sampling rates, we examined the multiple TR dataset introduced previously. In contrast to the GLM using the canonical HDR, we conducted a GLM using the finite impulse response (FIR) approach with a window of approximately 12 seconds in response to the 5 stimulus conditions (0 to 40% phase) for the separate face detection and fixation detection runs. We then extracted the FIR responses from a ROI that consisted of the primary visual cortex and compared all voxels FIR responses across all phases for the face detection against the fixation task (Figure 3).

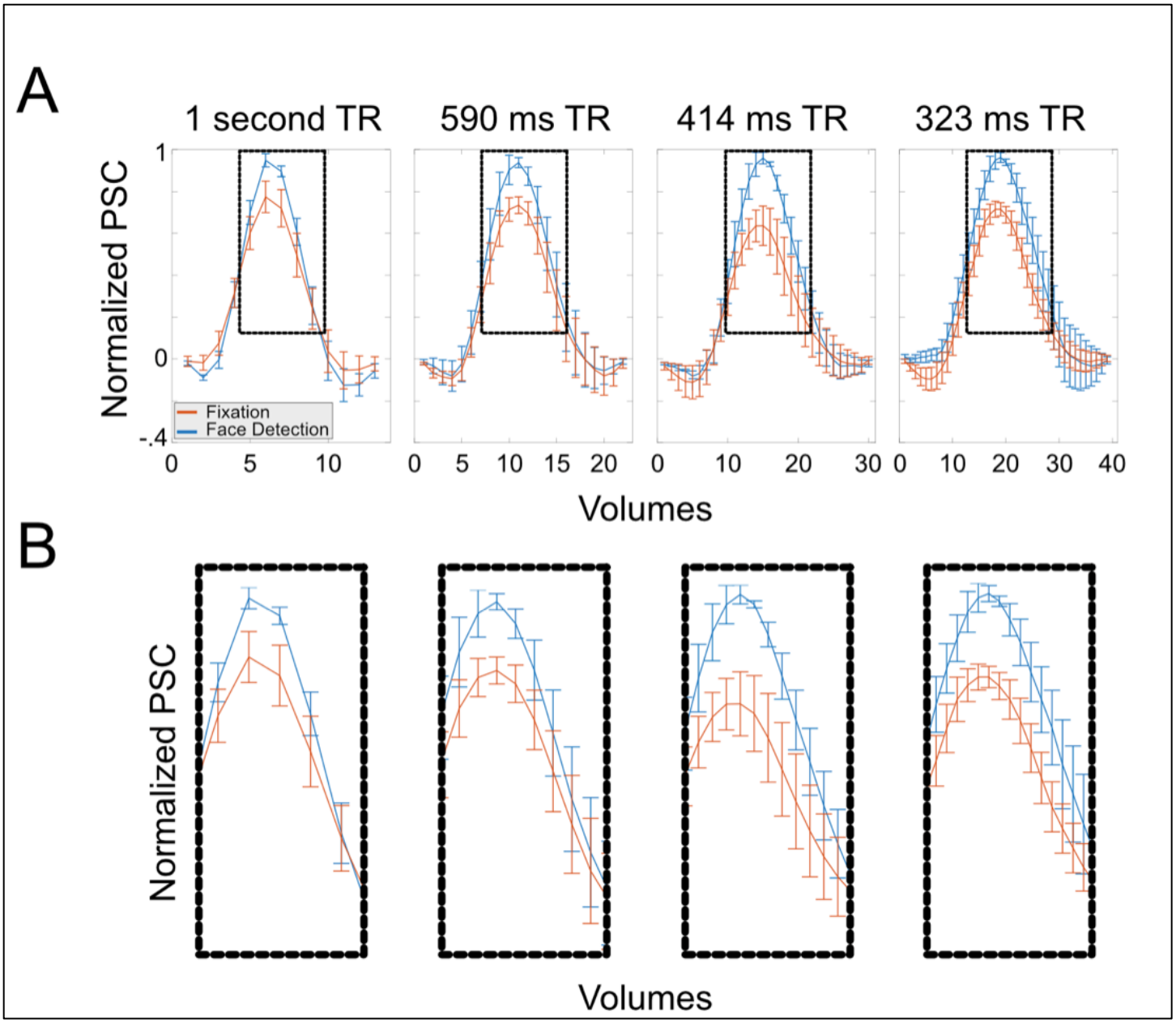

Figure 3. Clearer task differences at faster sampling rates. A) Panel A shows the average FIR (mean across subjects and phase coherences) for all resolutions elicited in the primary visual cortex during fixation and face detection task. Error bars portrays standard errors across subjects **B)** Zoomed in version of the dotted boxes in panel A. Note: 1. how latency differences across tasks become more prominent as TR decreases; 2. How amplitude difference across tasks also become more pronounced as TR decreases.

Our data indicate that as sampling rates increase, a more precise characterization of the HDR leads to a more precise quantification of temporal differences across tasks. Consider the 1 second TR acquisition (Figure

3, First column) in which 2 timepoints corresponding to peak of the curves can be seen as differentially responding to the 2 tasks (shown in different colors - column 1, lower; non overlapping error bars). For the 1 second TR, the HDR elicited by the face detection and fixation task are nearly perfectly overlapping, indicating no temporal differences across tasks. As we examine time courses with faster sampling, not only do we see more timepoints differentially responding to the 2 tasks (culminating in in 12 or more timepoints at a sampling rate of 0.323); but also, importantly, we begin to appreciate differences in the temporal structure of the HDRs (Column 4). More specifically, the response elicited by the fixation task drops off faster than that elicited by the face detection task (clearly seen for the .414 s and the .323 s TRs). Though preliminary, these findings highlight one of the benefits of rapid sampling in increasing the discriminability of task effects on the basis of HDRs estimate and show how this effect varies over the duration of the response.

Moreover, as we sample data faster more prominent temporal structure can be appreciated. For example, for the fixation task, the amplitude of the initial dip increases as a function or temporal resolution, ranging from an average amplitude of approximately -.01±0.036 (mean ± standard error) for the 1 second TR to -0.093±0.047 for the 0.323 second TR (Figure 4, Top). Here we are showing an improved ability to detecting early temporal structure (i.e., initial dip) as TR decreases, however, these datasets varied across several parameters, including in their spatial resolution and tSNR characteristics. This was done to ensure that image SNR was maximized and comparable across protocols (see Figure 1). To further compare temporal characteristics across temporal resolutions only (that is, keeping all other parameters constant), we simulated 3 slower TR datasets by downsampling the 323ms data. These were produced by averaging 2, 3 or 4 neighboring timepoints to produce simulated data with effective TRs of 646, 969 and 1292ms. Identical processing method and analyses were conducted to determine how this change in sampling affected the observation of the initial dip (Figure 4, middle row). Despite being derived from the 323ms data, which possess a robust initial dip, we observed that downsampling the data dramatically reduced (646ms data) or

eliminated this effect (969 or 1292 data). These findings suggest that sampling rates are driving these effects, and it is not an artifact of the changing voxel size or tSNR characteristics.

More importantly, also as a function of temporal resolution, our analyses indicated early emergence of attentional differences during the period of the initial dip. We found that, for the fastest resolution only, all subjects showed task differences emerged as early as 5 TRs (i.e., ~1.62 secs) after stimulus onset (Figure 4, Bottom row), with larger responses (i.e., more negative) for the fixation (amplitude: -0.095±0.053 at TR 5) than the face detection task (amplitude: 0.01±0.027 at TR 6). These timings are consistent with those reported for the initial dip (Hu et al., 1997; Menon et al., 1995) and shows that sufficient temporal sampling is required to detect such rapid and (across all subjects – see Figure 4) small attentional effects.

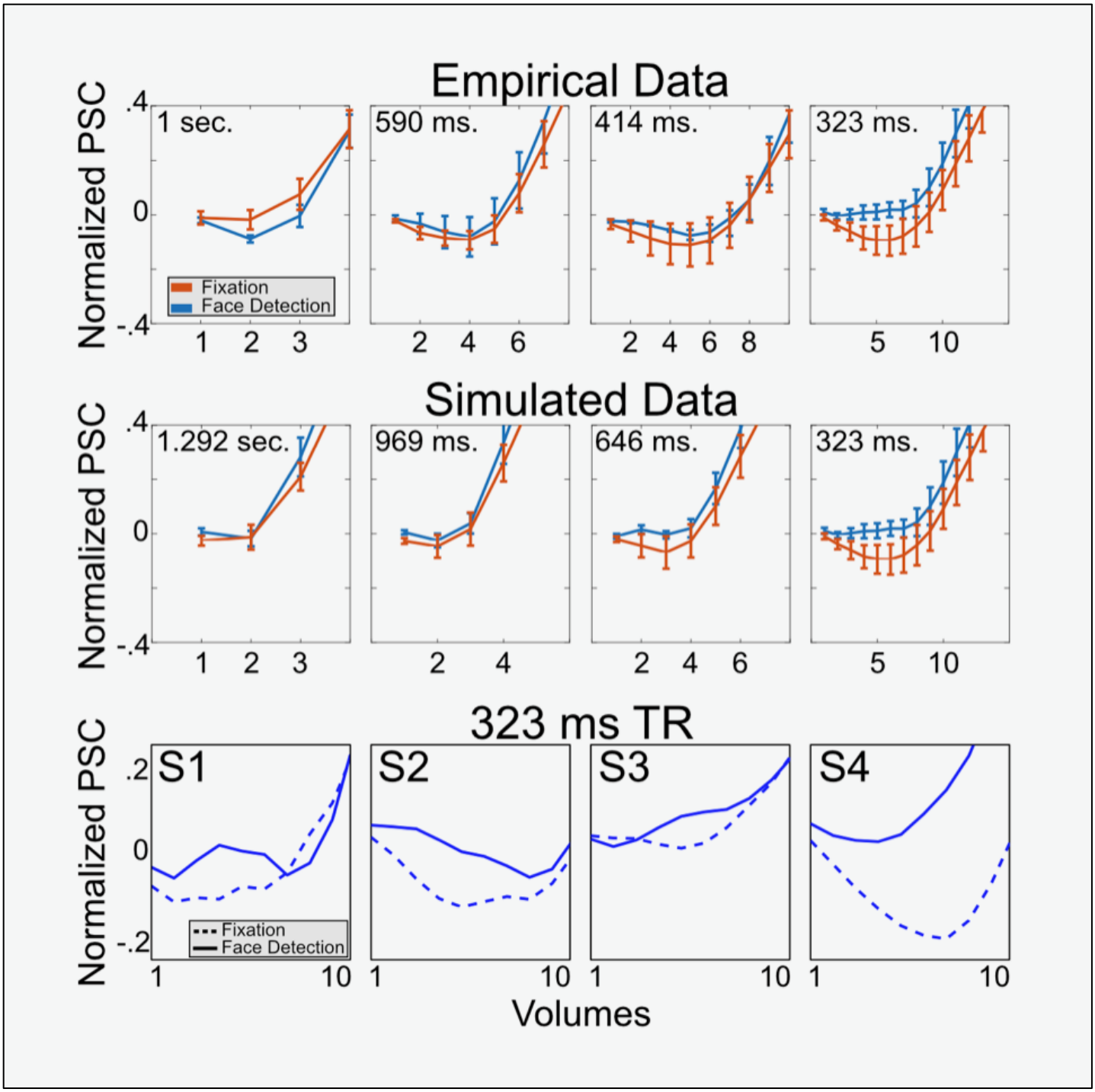

Figure 4 Clearer emergence of initial dip with sampling rate increases. The top two panels illustrate how the initial dip becomes more pronounced as TR decreases. Specifically, task differences in the initial dip only emerge at the fastest sampling rate (i.e., 323ms TR). Both top panels zoom in the initial dip for the average FIRs across subjects and conditions elicited by both tasks in the visual cortex ROI, with error bars representing standard error across subjects. **The top panel** shows the initial responses in the empirical data for all resolutions (as portrayed in Figure 3). **The middle panel** instead

shows downsampled data, simulating different TRs. Note the striking correspondence between empirical and simulated data. **The bottom panel** instead shows the first 10 volumes (i.e., 0 to 3.23 seconds after stimulus onset) for each single subject and for both tasks, only for the 323 ms TR data (i.e., the fastest temporal sampling), which the data set showing the earlies differences across tasks. Note how all subjects show an increased negativity for fixation compared to face detection.

The initial dip, which was noted to begin within the first second of a BOLD response (Menon et al., 1995)(Hu et al., 1997), has been difficult to confirm (Buxton, 2001), with a number of studies not being able to identify this temporal component, despite ample averaging (Fransson et al., 1999, 1998). A number of variables appear to contribute to the difficulty of finding the initial dip, including field strength, task timing, stimulus type and spatial and temporal dimensions of the sampled data (Hu and Yacoub, 2012; Watanabe et al., 2013). Here, we provide additional evidence in support of the importance of sampling rate in identifying the initial dip. It is if course plausible that subtle differences between the task conditions in early visual cortex are giving rise to temporal differences in the initial dip and more generally across the HDR. As such, with typical acquisition strategies this effect is missed (Figure 4, first column), leading to incorrect assumptions about task demands or task effects. While the initial dip has been suggested to reflect more localized neuronal responses (Hu et al., 1997; Menon et al., 1995; Yacoub and Hu, 2001) occurring immediately after the stimulus, we report that attentional differences related to task can also be visible in the initial dip.

As the data presented here are meant to provide insights into the temporal dimension of BOLD responses, a thorough neuroscientific interpretation of these results is beyond the scope of this work. However, the differences in the amplitude of the initial dip across tasks could be related to response inhibition during the fixation task, where faces are considered as distractors and must be suppressed.

Generally, we report both early (i.e. 5 TR after stimulus onset) and late (after the HDR peak) latency differences become clearer as temporal resolution increases. Albeit preliminary, due to the small N, these

promising results suggest that, if fine grained temporal information is available, faster temporal sampling may uncover additional temporal structure or stimuli related effects that were previously overlooked. Of course, finding such effects may require specific analysis strategies tailored for voxel wise HDRs and single trial estimates of responses.

Temporal Dynamics in fMRI

Until recently, rapid (i.e. sub-second) temporal dynamics in fMRI have been for the most part relegated to a less important role and, accordingly not much attention has been given to statistical analyses of TR-to-TR fluctuations in the sub-second regime. For example, in the realm of spatial analyses, considerable attention has been given to spatial clustering (Cox et al., 2017; Eklund et al., 2016; Hayasaka and Nichols, 2003; Nichols, 2012), including using Monte Carlo methods (Cox et al., 2017). Advanced multivariate methods have also been developed to account for *spatial* patterns of activity (Haxby et al., 2014, 2001), including using search light approaches (Kriegeskorte et al., 2006). Notably, these spatially oriented methods can also benefit from temporal detail. For example, Vu and colleagues demonstrated that accurate word timing, made possible by fast TR fMRI data, improved the performance of multivoxel pattern analyses (MVPA) (Vu et al., 2016).

Recently, however, there has been some development in methods which directly consider temporal dynamics. For example, when considering deconvolution approaches, it is necessary to correctly deal with the multiple levels of statistical interdependence. A voxel-wise, linear mixed modeling approach was developed to examine both where and when statistical differences occur in complete HDRs (Chen et al., 2015). The benefit of this method is that it allows the statistical examination of a full curve, rather than summarizing the multiple parameter estimates via averaging or area-under-the-curve calculations. This becomes increasingly important as sampling rates and thus the number of timepoints estimated in the deconvolution increase.

Analogous to multivariate pattern analysis for spatial maps, a recently developed method considers the temporal corollary of this, termed temporal MVPA (tMVPA) (Vizioli et al., 2018). tMVPA uses single trial

response time courses or single run FIR estimates to compute single trial Representation Dissimilarity Matrices (RDM) independently per condition within a given ROI. To infer statistically significant differences across time courses, tMVPA builds on a sliding window approach (extensively tested on real and synthetic data elsewhere – (Vizioli et al., 2018)) that allows for the precise identification of the temporal window of an effect and whether this encompasses only a few time points or is sustained over a larger time window. Multivariate analyses methods have been shown to have increased sensitivity for the analyses of spatial maps (Kriegeskorte and Bandettini, 2007; Vizioli et al., 2020a) in fMRI. There is evidence that this is also the case for the temporal domain, with prior work finding earlier identification of statistically significant task differences on both real (Ramon et al., 2015) and synthetically simulated data (Vizioli et al., 2018).

Partial windowing of temporal effects

Partial volume effects (i.e. when the prescribed voxel size is not small enough to capture only a single tissue) are often discussed in the fMRI literature. This describes a phenomenon in which a single voxel can have contributions from multiple tissue types, or from two nominally independent cortical layers (Siero et al., 2013). In the temporal domain, a parallel manifestation of this is aliasing of oscillatory signals due to sampling slower than the Nyquist frequency. This is typically considered in the context of physiological noise regressors, such as cardiac pulsation (Chen et al., 2019). For example, cardiac signals, which tend to range between 0.8 to 1.5Hz require rapid sampling rates in order to avoid aliasing, even faster than what is used for increasingly common sub-second TRs. While rapid sampling does improve the fidelity of these signals and aid in their removal (Chen et al., 2019; Tong et al., 2014) we wish to highlight additional considerations beyond undesirable physiological noise.

Unlike periodic physiological signals, there is often little consideration of any loss of task relevant BOLD signal information due to insufficient temporal sampling. However, given the rich dynamics of the BOLD signal and the short delay between a stimulus and a potential initial dip or initial rise in signal intensity, there is a risk

that insufficient sampling rates can lead to “partial windowing” of temporal signals of interest. This effect can manifest due to their short duration and magnitude, as is the case for the initial dip. To some extent, this can be mitigated by jittering the stimulus onset with respect to TR (Amaro and Barker, 2006; Dale, 1999; Miezin et al., 2000; Watanabe et al., 2013), but this requires jittering with sufficient time steps in order to capture all temporal aspects of interest, i.e. on the order of 500 ms or shorter. Considering the duration of a conventional HDR (on the order of 20s), this would require multiple stimulus presentations to capture a single “full” HDR, producing overly long scan times or reduce repeats of the stimulus. This is also not to say that faster acquisition times cannot take advantage of jitter, however, they would require substantially fewer variants of the stimulus timing to sample all of the temporal characteristics of interest, thereby reducing “partial windowing” effects. If sampling is sufficiently fast, then the effect of partial windowing is reduced even further, producing estimates of the HDR that capture fast temporal dynamics (Figure 4, above).

High frequency and dynamic correlations in resting state

If the effects of interest are oscillatory in nature, then jittering is no longer a reasonable option and instead rapid acquisitions may be more suited for observing high frequency effects. For example, in resting state fMRI, the primary frequencies of interest appear in low frequency bands, between 0.1 and 0.01Hz. For these frequencies, faster sampling primarily serves to reduce the impact of physiological noise, as discussed previously. Such low frequency bands are easily sampled with classic 2 to 3 second TRs and would, by necessity, contain substantially higher relative power when compared to high frequency fluctuations. Recently, however, with the advent of faster sampling, there have been observations of resting state correlations at frequencies greater than 1Hz (Gohel and Biswal, 2014; Smith-Collins et al., 2015). Though this work is still ongoing, there are methodological concerns as denoising procedures make it possible to reintroduce noise under the linear regression framework (Lindquist et al., 2019) and even produce spurious or enhanced high frequency correlations (Chen et al., 2016).

One argument against high frequency correlations concerns the plausibility of their origin. Based on conventional models of the BOLD response, it should be incredibly difficult to detect neuronally driven oscillations at such high frequencies (Chen et al., 2016), however it has been suggested that through suitable task designs it is possible to derive information from effects in the 10s of millisecond range (Ogawa et al., 2000). This is ultimately an empirical question that can be evaluated using oscillating stimulus designs with sufficiently high frequencies. Unlike *relative timing* within regions or between separate tasks and stimuli, oscillatory or incredibly rapid stimulus presentation is much more difficult to detect. This is due to the plateauing nature of the BOLD response, converting these rapid oscillations into small fluctuations. Recent work has uncovered that with sufficiently fast sampling, fMRI can capture rapid oscillations in visual stimuli up to 0.75 or potentially 1Hz (Lewis et al., 2016) and other have found that neurovascular coupling appears to occur on shorter timescales than were typically thought (Siero et al., 2011; Silva and Koretsky, 2002). How these findings have led to a reconsideration of the dynamics of the HDR and its underlying biological principles are considered in a separate manuscript in the current issue (Polimeni, and Lewis, 2021).

An alternative extension to resting state analyses, known as *dynamic functional connectivity* (dFC), consider the change in the correlation pattern over time, often within sliding windows containing 30 to 60s worth of samples (Hutchison et al., 2013; Preti et al., 2017). These studies seek to explore how brain states change, in contrast to static functional connectivity which captures a single measure of correlations across the brain. This approach has been used, for example, to link behavioral measures of executive performance with the changes in network state (Braun et al., 2015) or link changes in the default mode network while listening to narratives with memory retrieval (Simony et al., 2016). One recurring question for a windowed approach concerns the window length. With a TR of 2 seconds, there is often a difficulty in selecting an adequate window length that balances statistical power concerns against capturing each dynamic state (Hutchison et al., 2013). Here the statistical gains of rapid sampling can be directly linked to the benefit of uncovering neural dynamics, as there is evidence that faster sampling provides for gains in measuring significant functional

connectivity changes within shorter and shorter windows (Sahib et al., 2018) or capturing network effects that are missed in static analyses of clinical populations (Zhang et al., 2018). Though resting state emerged as a methodology focused on slow (0.1 to 0.01Hz) oscillations for which typical 2s TRs are more than adequate, these findings suggest that there are substantial benefits and novel neuroscientific findings waiting to be uncovered with fast fMRI.

Relationship between spatial specificity and the temporal signal.

While much of fMRI has pushed for higher and higher spatial resolutions, there is also a need to consider how temporal dynamics interact with spatial precision as a specific point in time gives rise to a non-stationary spatial activation map. For example, we know that the HDR changes across regions, but also within regions across cortical depths. It would be logical to assume that when temporal sampling is too low, accurate characterization of the model HDR (or of the empirical time courses themselves) would be unachievable. Consequently, model fit may be suboptimal, leading to misestimation of response amplitude parameters, thus producing inaccurate spatial maps. Here, we consider further implications for spatial resolution and specificity in the context of temporal information.

Depth-Dependent fMRI and Spatiotemporal Information

There is evidence that early and late phases of the HDR have greater spatial specificity relative to the central peak (Goodyear and Menon, 2001; Puckett et al., 2016; Shmuel et al., 2007). In line with this, it was proposed that fitting or analyzing just the early parts, such as the initial dip, could provide a method to gain spatial specificity (Hu et al., 1997; Menon et al., 1995; Yacoub and Hu, 2001). A similar possibility manifests in depth-dependent fMRI data. As venous blood drains through the cortical column, there is a slight delay between the peak of deep layers and the large veins on the pial surface (Petridou and Siero, 2019; Siero et al., 2011, 2015; Silva and Koretsky, 2002). This effect appears as differences in the HDR between layers, which

must be accounted for in analyses. Using an identical model for the HDR across all layers will lead to mismodelling (Lindquist et al., 2009) and could produce spurious layer dependent effects if the temporal differences appear as amplitude changes. Alternatively, as a consequence of the same mismodelling, the true effects, which are often very small in magnitude, could be missed. HDR estimates must be carefully tailored for each layer in order to make depth dependent inferences about neural connections or activity.

Building on this idea, it is has been recently demonstrated that we can use this temporal information to separate out the earlier responses, which may be nominally more spatially precise, from the later responses (Kay et al., 2020). This method, termed temporal decomposition through manifold fitting (TDM), uses unbiased FIR estimates of voxel time courses to produce two regressors for each event, one early and one late. This method separates out these responses rather than accounting for timing differences, as is done with methods that use multiple basis functions. While this method works with data sampled at sampling rates of up to 2.2 seconds, the time courses of early and late responses are highly correlated, and higher temporal sampling would aid in separation and provide more data dimensionality for estimating early and late responses. More work is needed to consider how spatial effects interact with the temporal domain and what resolutions are required for an optimal experimental paradigm. It is likely that reduced field of view imaging will remain common, as whole brain imaging at both high spatial and temporal resolutions remains difficult.

Conclusion

Technical developments and the increasing availability of advanced pulse sequences and methods have made ultra-fast fMRI routinely possible. Here, we have tried to address a seemingly straightforward question – What are the benefits of increased temporal sampling for fMRI? In combining information from existing work and our own empirical demonstrations we have shown that the answer is complex, but ultimately encouraging. We have argued that the benefits are not just limited to statistical gains, but encompass a wide range of potential neuroscientific questions, including BOLD dynamics at rapid timescales. While we find

consistent effects across subjects and convergence with emerging data, additional work with larger sample sizes will be required to confirm the specific timing of the effects reported. Nonetheless, these preliminary results provide a conceptual demonstration that faster temporal sampling can help extract fine grained temporal information, if this is available. Of course, additional considerations are needed regarding the challenges and difficulties associated with collecting, analyzing and interpreting rapidly sampled data. Nevertheless, the potential benefits are many: statistical power, better denoising, better spatial resolution and, importantly additional and more precise insights into neuronal temporal dynamics. Though space and time are intrinsically linked in fMRI, the relationship between accurate measures of temporal dynamics and spatial precision is often overlooked. More precise timing estimates can produce better models, which in turn will produce more accurate spatial maps. Collectively this diverse array of benefits suggests the continued work is worth the effort. With the combined efforts across hardware, pulse sequence developments, statistical understanding and methodological approaches the functional neuroimaging field is ready for a resurgence or perhaps a return, to the days of in depth, temporal investigations.

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