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Representation of shape, space, and attention in monkey cortex

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ABSTRACT

Attentional deficits are core to numerous developmental, neurological, and psychiatric disorders. At the single-cell level, much knowledge has been garnered from studies of shape and spatial properties, as well as from numerous demonstrations of attentional modulation of those properties. Despite this wealth of knowledge of single-cell responses across many brain regions, little is known about how these cellular characteristics relate to population level representations and how such representations relate to behavior; in particular, how these cellular responses relate to the representation of shape, space, and attention, and how these representations differ across cortical areas and streams. Here we will emphasize the role of population coding as a missing link for connecting single-cell properties with behavior. Using a data-driven intrinsic approach to population decoding, we show that both 'what' and 'where' cortical visual streams encode shape, space, and attention, yet demonstrate striking differences in these representations. We suggest that both pathways fully process shape and space, but that differences in representation may arise due to their differing functions and input and output constraints. Moreover, differences in the effects of attention on shape and spatial population representations in the two visual streams suggest two distinct strategies: in a ventral area, attention or task demands modulate the population representations themselves (perhaps to expand or enhance one part at the expense of other parts) while in a dorsal area, at a population representation level, attention effects are weak and nearly non-existent, perhaps in order to maintain veridical representations needed for visuomotor control. We show that an intrinsic approach, as opposed to theory-driven and labeled approaches, is useful for understanding how representations develop and differ across brain regions. Most importantly, these approaches help link cellular properties more tightly with behavior, a much-needed step to better understand and interpret cellular findings and key to providing insights to improve interventions in human disorders.

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1. Attention: single-cell versus population representations

Attention is a critical component of executive functions (Lyon & Krasnegor, 1996; Sereno & Bolding, 2017). Executive functions are a set of cognitive functions that are essential for goal-oriented behavior and drive our ability to adapt to a constantly changing environment. Executive function deficits lead to disproportionate impairment in function and activities of daily living (Cahn-Weiner, Boyle, & Malloy, 2002; Rabinovici, Stephens, & Possin, 2015). Attention is essential in order for individuals to generate thought, to think flexibly, to update and manipulate information, to inhibit what is irrelevant, to self-monitor, and to plan and adjust behavior as appropriate to the present context (Jurado & Rosselli, 2007; Rabinovici et al., 2015). Attentional deficits are a hallmark characteristic of numerous developmental (e.g., Jeter et al., 2015; Kirchgessner, Chuang, Patel, & Sereno, 2015; Sweeney, Takarae, Macmillan, Luna, & Minshew, 2004; Willcutt, Doyle, Nigg, Faraone, & Pennington, 2005), neurological (e.g., Fischer et al., 2016; Yarnall, Rochester, & Burn, 2011), and psychiatric human disorders (e.g., Babin et al., 2011; Levin, 1984; Ottowitz, Dougherty, & Savage, 2002). In a review of attention research from the past century, Driver (2001) noted that one of the most promising recent developments in the field was the increasing interplay between psychology and neuroscience from both experimental psychologists and neuropsychologists, such as Allport, Posner, Rafal, and Robertson (e.g., Allport, 1987; Posner, Snyder, & Davidson, 1980; Rafal, 1994, 1996; Robertson & Marshall, 1993). Driver (2001) emphasized that these researchers, by combining various ideas and approaches, produced work that led to substantial progress in understanding and treating patients with attentional deficits.

Given attention's key role in human disease, much research in primate neurophysiology has focused on that subject. In fact, beginning with some of the earliest recordings in primates, attentional modulation of neural responses was documented nearly a half a century ago (e.g., Goldberg & Wurtz, 1972; Wurtz & Goldberg, 1972). Over the decades a variety of effects have been demonstrated at a cellular level, from changes in gain (e.g., Colby, Duhamel, & Goldberg, 1996; McAdams & Maunsell, 1999) to changes in the statistics of stimulus responses (e.g., decreases in Fano factor or noise correlations between neurons; Cohen & Maunsell, 2009; Mitchell, Sundberg, & Reynolds, 2007) to documentation of competitive effects with multiple stimuli (e.g., Luck, Chelazzi, Hillyard, & Desimone, 1997; Motter, 1993; for a review see Sereno & Lehky, 2018).

Most of this physiological work in attention has focused on responses at the single-cell level, often centered on issues of single-cell modulations of signal-to-noise ratios as indicators of salience. Less work has focused on how attention might influence or change the neural population representations of stimuli, either of stimulus shape (but see Çukur, Nishimoto, Huth, & Gallant, 2013) or stimulus location. Going beyond that, even less physiological work has directly compared attentional changes between these neural population representations across cortical regions or visual processing streams. Our interests have centered on the latter issue, comparing population representations in different cortical regions, in particular comparing populations associated with the ventral visual stream [commonly associated with object recognition (Kravitz, Saleem, Baker, Ungerleider, & Mishkin, 2013; Tanaka, 1996)] and the dorsal stream [commonly associated with representations of space linked to visuomotor control (Gallivan & Goodale, 2018; Kravitz, Saleem, Baker, & Mishkin, 2011)].

In order to improve interventions in human disorders, it is critical that we be able to link low-level cellular effects (single-cell neurophysiology) more tightly with high-level behavior. We approached this linkage through an intermediate population coding approach, based on a data-driven or exploratory approach to data analysis (Martinez, Martinez, & Solka, 2012; Mazzocchi, 2015; Tukey, 1980), which we have labeled or characterized as an *intrinsic* approach (Lehky, Sereno, & Sereno, 2013). Furthermore, we then used these population-coding techniques to compare cortical regions that have not been often directly compared. Using such a novel approach, we sought to better understand and interpret cellular findings with the expectation of providing insights into the representation of shape, space, and attention across cortical regions. A better understanding of the representation of attention is certain to improve interventions in human disorders.

2. Representations: extrinsic versus intrinsic approaches

Perceptual and cognitive representations are encoded in a collective fashion by populations of neurons and not individual neurons in isolation. Dealing with the collective behavior of neural populations leads to complex and sometimes non-intuitive properties that often require extensive quantitative methods to characterize. This has led to a widespread theoretical literature dealing with population codes, (e.g., Averbeck, Latham, & Pouget, 2006; Deneve, Latham, & Pouget, 1999; Földiák, 1993; Jazayeri & Movshon, 2006; Oram, Földiák, Perrett, & Sengpiel, 1998; Pouget, Dayan, & Zemel, 2000; Quian Quiroga & Panzeri, 2009; Sanger, 2003; Seung & Sompolinsky, 1993; Zhang, Ginzburg, McNaughton, & Sejnowski, 1998).

We previously defined two classes of population coding models, termed *extrinsic* and *intrinsic* coding (Lehky et al., 2013; see also Brette, 2019, for similar discussion). The distinction was defined by two conceptual properties, namely *labeling* and *atomism*. Labeling means that each individual neuron in a population is characterized (or *labeled*) by a parametric model fit to its neural responses (e.g., a Gaussian tuning curve for stimulus orientation or spatial location in world coordinates). This label, or set of parameters, specifies each neuron relative to an external framework attached to the physical world, hence such coding is *extrinsic*. Atomistic means that within a population code the properties of each neuron is self-sufficient and not defined by relationships between neurons (note that atomistic doesn't mean that there aren't influences, either deterministic or statistical, between neurons in a population). The opposite of atomistic is relational. Extrinsic coding is the most common type of population coding model,

and all the models listed in the previous paragraph are extrinsic.

Intrinsic population coding, on the other hand, is characterized by being unlabeled and relational. *Unlabeled* means that neural activities are not labeled by a set of parameters defined by external models or referenced to an external physical frame of reference. Rather, neural activities are internally referenced relative to each other (hence the analysis is intrinsic). The prototypical example of intrinsic population coding is multidimensional scaling (MDS) (Hout, Papesh, & Goldinger, 2013; Izenman, 2008; Shepard, 1980), a multivariate statistical technique which can be used to reduce the dimensionality of large neural populations so that geometric relationships between stimuli within a high-dimension neural representation space become apparent. Our own work examining population coding for shape, location, and attention uses an intrinsic approach and is based on MDS.

The distinction we make between extrinsic and intrinsic models of population coding overlaps with the distinction made by Tukey (1980) between two basic styles of statistical data analysis: confirmatory analysis and exploratory analysis. The most widespread approach is confirmatory data analysis, based on the use of hypothesis testing, confidence intervals, and pre-defined classes of statistical models to fit the data (e.g., Gaussian distributions). In this manner, confirmatory analysis relates to extrinsic population code models. On the other hand, exploratory data analysis (Martinez et al., 2012), whose popularity is growing as computational power becomes more available, has methodology in common with intrinsic population coding models. In fact, multielectrode techniques are a good fit for exploratory data analytic techniques, and intrinsic methods, in particular, and there is great potential to more closely integrate these advanced data analysis techniques with advanced data acquisition technologies. Data-driven exploratory analysis includes, among other things, scientific visualization and dimensionality reduction approaches. MDS is prominent in exploratory analysis and central to many intrinsic population coding models.

There is obviously a place for both hypothesis-based and data-driven exploratory methods for data analysis. One benefit of an unlabeled approach, particularly when dealing with efforts to understand high-dimensional data, is that it is less subject to pre-conceptions and unconscious biases. Ultimately, data-driven analysis would be expected to be followed by more conventional hypothesis-based approaches, with perhaps data-driven analysis and hypothesis-based approaches reinforcing each other. It is important to note that data-driven exploratory methods can be evaluated, compared, and validated to examine if different sets of data have similar or different structure or, in some cases, how they compare with 3D physical space when dealing with stimulus locations. For example, we have used a Procrustes transform to compare the low-dimensional spatial map implicit in a small neural population to veridical physical space to see how accurate intrinsic analyses of a small population of neurons were at recovery of target locations (e.g., Sereno & Lehky, 2011a). In addition, bootstrapping can be used to estimate variance or performance of a model [e.g., comparison of stress or error values of low dimensional MDS manifolds recovered from neural populations recorded from different cortical areas (see Sereno, Sereno, & Lehky, 2014)]. We have previously argued and shown with modeling that optimal receptive field characteristics for coding visual space are strikingly different depending on whether intrinsic or extrinsic population coding is used (Lehky et al., 2013). Namely, for intrinsic coding, large RFs (receptive fields) are best, whereas for extrinsic coding, when each neuron is labeled with the spatial location of its RF, then small RFs can produce more accurate representations of space than large RFs. Study of patients with brain lesions in neuropsychology indicates that various higher-level cortical areas with large RFs are important in spatial representations (Jeannerod & Jacob, 2005), perhaps suggestive of intrinsic coding. For additional discussion of the advantages (e.g., inherent categorization and discrimination; invariances) and disadvantages (e.g., not grounded to physical measures) of intrinsic, as opposed to extrinsic, approaches, see earlier review by Lehky et al. (2013).

Our own work examining population coding for shape, location, and attention uses an intrinsic approach and is based on MDS of populations of single-cell recordings. In modeling (Lehky & Sereno, 2011), we show that completely correlated noise amongst cells in a population has no effect on MDS analyses of stimulus locations while uncorrelated noise introduces some distortion. Observed experimental values of noise correlations are very low, in the range .05–.10, in cortical area V4 (Cohen & Maunsell, 2009, 2011). Based on such low observed levels of noise correlation we estimate a small amount of distortion in MDS decoding. Hence, noise correlations at physiological levels do not seem to greatly affect application of these approaches when using simultaneous recordings, including laminar recordings.

Various intrinsic population coding data analyses related to visual processing have employed multidimensional scaling and other related dimensionality reduction techniques. These include electrophysiology studies centered on an MDS analysis (Baldassi et al, 2013; Chang & Tsao, 2017; Eifuku, De Souza, Tamura, Nishijo, & Ono, 2004; Kayaert, Biederman, & Vogels, 2005; Kiani, Esteky, Mirpour, & Tanaka, 2007; Murata, Gallese, Luppino, Kaseda, & Sakata, 2000; Op de Beeck, Wagemans, & Vogels, 2001; Rolls & Tovée, 1995; Young & Yamane, 1992) as well as fMRI studies (Bracci & Op de Beeck, 2016; Connolly et al., 2012; Kravitz, Peng, & Baker, 2011; Kriegeskorte et al., 2008b). Similar to the electrophysiology studies, the intrinsic fMRI approaches use a combination of RSA [Representational Similarity Analysis; see Kriegeskorte, Mur, and Bandettini (2008a)], multidimensional scaling (MDS), and hierarchical cluster analysis. However, most fMRI studies use extrinsic, model-based population decoding methods such as MVPA (Multivoxel Pattern Analysis) and combined RSA and model-based analyses [see Haxby, Connolly, and Guntupalli (2014) for a review]. Together, these studies reflect a predilection in the field towards focusing on shape (or scene) and not spatial representations [though see Hori et al. (2003) for use of MDS applied to spatial representations in hippocampus].

Our work extends these intrinsic population approaches in neurophysiological data to space as well as shape in visual areas, under identical experimental conditions including an

attentional manipulation, and furthermore has critically compared multidimensional scaling analysis in multiple cortical areas (including the ventral visual stream, dorsal visual stream, and prefrontal cortex) (Lehky, Peng, McAdams, & Sereno, 2008; Lehky & Sereno, 2007; Peng, Sereno, Silva, Lehky, & Sereno, 2008; Sereno & Amador, 2006; Sereno & Lehky, 2011a; 2018; Sereno & Maunsell, 1998; Sereno et al., 2014).

Importantly, MDS is one of the oldest and most widely used non-linear dimensionality reduction methods that are available (Hout et al., 2013; Izenman, 2008; Shepard, 1980). No claims are made that the brain is implementing these dimensionality reduction algorithms. We are using MDS as a data analysis tool to tell us what information is available implicitly encoded in a low-dimensional space embedded within population activities. We suggest the brain is making use of that information. The low-dimensional information could remain embedded in the original high-dimensional neural response space, in which case there is no need to physically implement any dimensionality reduction algorithm. The low-dimensionality information would then be a virtual mathematical structure defining interactions with other high dimensional networks, ultimately connecting to high-dimensional motor networks. Alternatively, it is possible that a dimensionality dimension reduction algorithm does occur physically. There are many ways to make use of the information and we do not claim on the basis of available evidence that the brain *is* or *is not* implementing any particular algorithm. We have argued previously (Lehky & Sereno, 2011; Sereno & Lehky, 2011) that for some purposes the ability to form a low-dimensional representation may be computationally efficient or may facilitate exchange of information. It may also be argued that it is the simplest or even most mathematically parsimonious description. It is possible that formatting the same information in different ways within a neuronal population can lead to changes in the nature, speed, and efficiency of the processing that is supported.

Again, we believe that a quantitative population coding analysis is critical in linking low-level cellular effects with high-level behavior. Furthermore, we believe that such a broad population analysis (making comparisons across visual streams and properties), exemplified by the intrinsic multidimensional scaling methods employed by our work, will be valuable in the interpretation of not just single-cell data but fMRI data as well.

3. Cortical streams: object recognition versus spatial processing

Much early research (e.g., Brown & Schafer, 1888; Ferrier & Yeo, 1884) supports the idea of a division in visual processing between a ventral and a dorsal cortical region, which subserve object (Fig. 1) and spatial (Fig. 2) vision, respectively. More recent work also demonstrates evidence for functionally and anatomically distinct multisynaptic streams or projections from striate cortex (Ungerleider & Mishkin, 1982). These distinct visual cortical streams were first characterized as a 'what' and 'where' stream (Macko et al., 1982; Mishkin, Ungerleider, & Macko, 1983; Ungerleider & Mishkin, 1982), although later findings detailing spatial deficits with respect to visuomotor control have also referred to the spatial stream as 'how' instead of 'where' (Goodale et al., 1994; Goodale & Milner, 1992). Additional work has suggested there are likely multiple sub-streams within these general divisions (e.g., Aflalo & Graziano, 2011; Rizzolatti & Matelli, 2003). Recently, Kravitz et al. (2013) identified six distinct cortical and subcortical systems arising from different parts of the ventral or object pathway. They also describe four roughly parallel (with some cross-talk) routes through occipital-temporal cortex that course through the STS, dorsal/lateral IT cortex, ventral/medial IT cortex, and medial temporal cortex. In earlier monkey studies, additional object-related sub-streams were identified in fMRI evidence (Sereno, Trinath, Augath, & Logothetis, 2002), which showed robust responses to 3D objects and surfaces defined by motion cues, not only in regions of the STS in the temporal lobe but also in regions of parietal cortex (Fig. 3). In addition to demonstrating that 3D shape-from-motion is processed in MT and cortical areas located deep in the temporal lobe anterior to MT (FST, and mid-to-anterior regions in the fundus and ventral bank of the STS), Sereno and colleagues (Sereno, Augath, & Logothetis, 2005) reported a medial versus lateral sub-stream distinction within the temporal lobe for the processing of shape from dynamic versus static cues. Namely, they reported greater neural activation in the medial STS (MT, FST, and mid-to-anterior STS) for 3D shape-from-motion compared to greater activation in nearby lateral regions along the lateral surface (V4, TEO, and TE) for 3D shape-from-shading and shape-from-contour. These results provide early functional evidence for parallel routes, in this case to extract 3D shape from static and dynamic cues, running through occipital-temporal cortex. The shape-from-motion dominant route likely corresponds to Kravitz et al. (2013) STS stream and the shape-from-static cue dominant route to their dorsal/lateral IT cortical route. Identification of multiple sub-streams has also occurred for the dorsal stream. Kravitz, Saleem, et al. (2011) proposed three distinct cortical systems arising from different parts of the dorsal or spatial pathway (see also Theys, Romero, van Loon, & Janssen, 2015).

4. Cortical streams: segregation of properties or segregation of function?

Notwithstanding proliferation and identification of sub-streams, the idea remains that cortical processing of visual information from the retina is anatomically segregated into two fundamental streams, ventral versus dorsal, important for object and spatial vision, respectively. Despite this consensus, evidence has accumulated from our own and others' work demonstrating object representations in the dorsal stream (Durand et al., 2007; Konen & Kastner, 2008; Lehky & Sereno, 2007; Murata et al., 2000; Peng et al., 2008; Perry, Tahiri, & Fallah, 2014; Peuskens et al., 2004; Sereno & Amador, 2006; Sereno & Maunsell, 1998; Sereno et al., 2002; Subramanian & Colby, 2014). Furthermore, retinal and eye position spatial selectivities have been demonstrated in ventral stream neurons (Bremmer, 2000; Lehky et al., 2008; Leuschow, Miller, & Desimone, 1994; Op de Beeck & Vogels, 2000; Rosenbluth & Allman, 2002; Sereno & Lehky, 2011a;

Fig. 1 – Ventral stream and object recognition. Schematic localization of visual pathways in the macaque monkey brain, with red arrows indicating major visual areas along the ventral pathway. Anterior inferotemporal cortex (AIT) is a high-level visual area in the ventral pathway, important for object recognition and memory, and thought to be important in both object generalization (e.g., 'chair') and object discrimination (e.g., identification of individual tokens of a particular chair). AIT extends from within the superior temporal sulcus down past the anterior medial temporal sulcus to the ventral surface of the brain (not visible in this diagram), and anteriorly from the posterior medial temporal sulcus.

Fig. 2 – Dorsal stream and spatial processing. Schematic localization of visual pathways in the macaque monkey brain, with blue arrows indicating major visual areas along the dorsal pathway. The lateral intraparietal cortex (LIP), located on the lateral bank within the intraparietal sulcus (IPS), is a high-level area in the dorsal pathway, important for spatial localization of stimuli and visual guidance of motor actions. In the figure, the label for LIP is placed next to IPS, although LIP is actually located on the lateral bank of the sulcus and not visible from a surface view. Similarly, the label for MT is placed next to superior temporal sulcus (STS), although MT is actually located in the posterior fundus of the STS and not visible from a surface view.

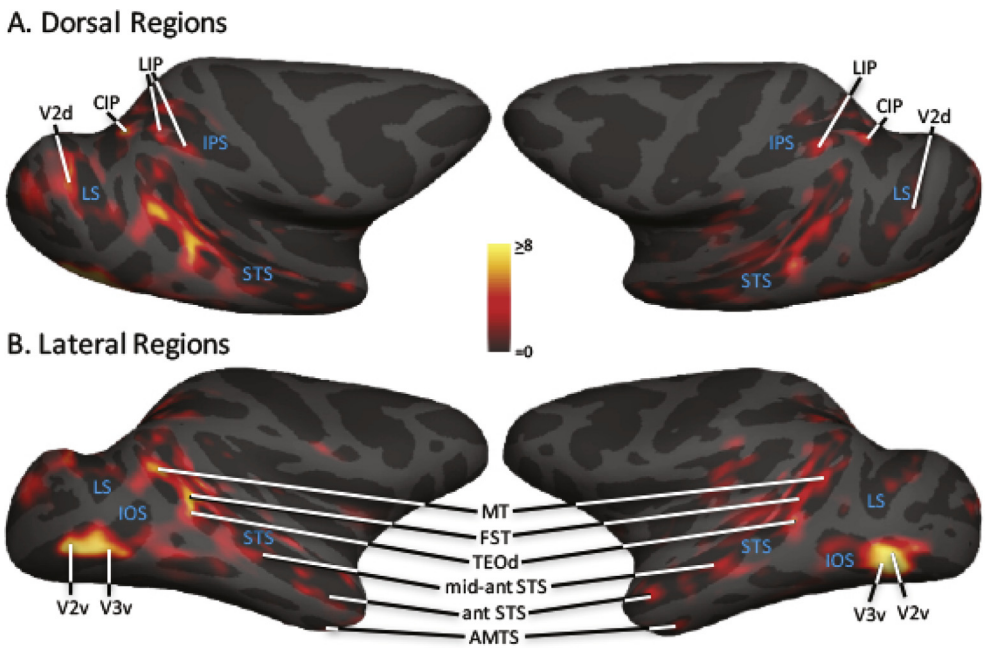

Fig. 3 – 3D Shape from motion in monkey dorsal and ventral stream regions. fMRI data were obtained from 13 slices oriented parallel to the STS (covering most of occipital, temporal, and parietal lobes) for the contrast between intact versus scrambled rotating random dot objects. Areas of activation are painted onto (A) dorsolateral and (B) lateral views of inflated right and left hemispheres. Major sulci are labeled with blue letters: LS (lunate sulcus), IOS (inferior occipital sulcus), IPS (intraparietal sulcus), STS (superior temporal sulcus). Cortical areas are pinpointed with white lines and labeled with black letters: V2v and V2d (visual area 2 ventral and dorsal), V3v (visual area 3 ventral), CIP (caudal intraparietal area), LIP (lateral intraparietal area), MT (middle temporal area), FST (floor or fundus of the STS), TEOd (area TEO dorsal), mid-ant STS (mid-to-anterior ventral STS), ant STS (anterior ventral STS), AMTS (anterior medio-temporal sulcus). The level of significance is indicated by the color bar which shows z-score values. Figure adapted from Sereno et al. (2002).

Sereno et al., 2014). Reports of *mixed* properties (i.e., object properties in dorsal and spatial properties in ventral) have muddied a clear distinction at the single-cell level between object and spatial properties in the ventral and dorsal streams, respectively.

As reviewed by Milner (2017), clear, albeit less profuse, interconnections between the two visual streams were recognized not only by the early connectional studies but also in more recent studies (e.g., Borra et al., 2008; Distler, Boussaoud, Desimone, & Ungerleider, 1993; Webster, Bachevalier, & Ungerleider, 1994; Zhong & Rockland, 2003). Perhaps due to these known interconnections, findings of these mixed properties have often been perceived as cross-talk (e.g., Perry et al., 2014) or inter-stream communication (Milner, 2017), and interpreted as necessary to provide integration (a sense of unitary vision) between two otherwise disparate streams (e.g., Budisavljevic, Dell'Acqua, & Castiello, 2018). Such cross-talk between streams could be mediated not only by changes in firing rates but also changes in neural correlations (Fries, 2005). Typically, then, object properties in dorsal stream are thought to derive from ventral stream projections and spatial properties in ventral stream are thought to derive from dorsal stream projections, with discussion focusing on where and how they integrate (e.g., Deco & Lee, 2004; Kravitz et al., 2013; Rao, Rainer, & Miller, 1997). This view that object properties derive from ventral stream and spatial properties derive from dorsal stream is apparent in the bias of published research, with physiologists and others using object- or feature-based tasks in ventral cortical areas and simple spatial or spatio-motor tasks in dorsal cortical areas. Across decades of research, few physiological studies make direct controlled comparisons of either object or space across streams under the same task or conditions.

In contrast, we have argued, and argue again here, that the distinction between the streams should not be seen so much as a segregation of properties (object *vs* spatial properties) but a segregation of function (object recognition *vs* visual-motor control for interaction or navigation through the world). In the ventral stream the function "object recognition" requires the incorporation of the property "shape" and the property "location". In the dorsal stream the function "visuomotor control" also incorporates the property "shape" and the property "location". What distinguishes a visual stream or cortical area is the functionality being implemented, not the sets of properties or parameters being used to construct that functionality.

We argue that the visual properties "shape" and "location" are independently elaborated in each of the two streams. This is in contrast to the widespread interactionist viewpoint, in which a complete representation of an image requires cross-talk or inter-stream communication between different streams. Under our viewpoint, what distinguishes the dorsal and ventral stream are not specializations for the different properties "shape" and "location" in the two streams. Rather, what distinguishes them are the ways that shape and location

are differently and independently constructed within each stream to achieve particular functions. Thus, we view that different cortical areas are defined by the function they subserve, and not primarily by different visual properties or parameters.

The properties associated with a particular function within a given cortical area are specified by input and output constraints embedded within the neural network computing that function. For example, the characteristics of "shape" in a ventral area are determined by how and which inputs are organized and/or selected from lower areas in the visual hierarchy, whereas "shape" in a dorsal area may have different characteristics depending on differences in how and which lower-level inputs are organized or selected. Analogously, the characteristics of "location" in a ventral and a dorsal area may be different reflecting the inputs and organization of their respective networks. The characteristics of shape and location properties in a given brain area are not just determined by the inputs from their neural networks, but also determined by their outputs to and feedbacks from higher-level cortical areas, in order to achieve the goals of those higher-level areas (Lehky & Sejnowski, 1988; Sereno, 1993).

Our assertion that shape and location are independently generated in dorsal and ventral streams is based on our work using intrinsic population coding methods (multidimensional scaling analysis, MDS; Section 2) of neurophysiological data, comparing shape and space representations in a ventral stream cortical area (AIT) and dorsal stream area (LIP). We find that shape representations in the ventral and dorsal area are not just scaled versions of each other in a neural shape representation, but rather show qualitative differences (Lehky & Sereno, 2007). For example, shape representations in the ventral stream show more conspicuous clustering of visually similar shapes than those in the dorsal stream. Although MDS had been previously used to separately examine population coding of shape representations in the ventral stream (e.g., Op de Beeck et al., 2001) and the dorsal stream (e.g., Murata et al., 2000), it was not until we had analyzed ventral and dorsal representations under identical experimental conditions in the same animals that it became possible to directly and quantitatively compare shape representations in the two streams. Similarly, we find that spatial representations in the ventral and dorsal streams are qualitatively dissimilar and not just attenuated versions of each other. In particular, we find that spatial representations in the ventral stream are *categorical* (more distorted but still having a topologically correct representation of location) whereas spatial representations in the dorsal stream are *coordinate* (having a very accurate and metric representation of location), following two classes of spatial representations independently established by Kosslyn and colleagues (Kosslyn, Chabris, Marsolek, & Koenig, 1992; Kosslyn et al., 1989). Such a direct and quantitative comparison between dorsal and ventral streams, both for shape and space, becomes feasible within a population coding framework.

To summarize, despite what may appear to be a mixing or amalgamation of shape and space parameters between ventral and dorsal cortical areas, we have proposed that the encoding and computations of those properties proceed to a significant degree separately and independently in each stream. Shape and space representations are generated within each visual stream in accord with the differing inputs and outputs and differing functional requirements of the streams.

5. Intrinsic advantages: data-driven categorization and discrimination

Intrinsic methods, using data-driven (agnostic) techniques such as MDS, are able to reveal relationships among individual neurons, such as category membership, without any *a priori* knowledge or assumptions about the properties of individual neurons beyond their firings (for example, without time-consuming measurements of neural tuning curves across a population) (Lehky et al., 2013). For fMRI data, the same data analysis techniques can be used, substituting voxels for neurons. Intrinsic approaches to analysis make explicit the geometrical relationships among different stimulus responses within the high-dimensional population representation space. Hence responses of neurons (or voxels) within the same category cluster in the same region of representation space. With a suitable dimensionality reduction technique, again such as MDS (but others are possible), the clustering of data points (neurons, voxels) into regions of the response space (i.e., categories) are frequently apparent simply through graphical inspection of plots of the representations of space, or for more complicated cases possibly using vector support machines to parse the representation space (Cortes & Vapnik, 1995). For intrinsic approaches, the relationships within the representation spaces are fundamental, and discriminations are determined by distances within the population response space. In contrast, in an extrinsic analysis, where data are processed atomistically rather than relationally, there is no innate basis for clustering and discriminating stimuli, and analysis proceeds by painstaking steps, including embracing various assumptions in the construction of a statistical model.

In our own physiological data, using an intrinsic approach (MDS) we are able to show and quantify how ventral stream neural populations themselves categorized or clustered our simple geometric stimulus patterns into three different groups (based only on their firing rates without measuring tuning curves), seemingly based on visual similarity (which we labeled having horizontal and vertical features, triangle-like, and doughnut-like shapes) (Lehky & Sereno, 2007). Likewise, categorization using MDS in neurophysiological data has been demonstrated in other single brain areas, including categorization of shape (faces and objects) in the monkey ventral stream (Baldassi et al., 2013; Eifuku et al., 2004; Kayaert et al., 2005; Kiani et al., 2007; Op de Beeck et al., 2001; Rolls & Tovée, 1995; Vogels, Biederman, Bar, & Lorincz, 2001; Young & Yamane, 1992), and categorization of shape (objects) in the dorsal stream (Murata et al., 2000; Romero et al., 2013).

In addition to allowing categorization based on regions of high-dimensional response spaces where stimuli cluster, the intrinsic approach can also quantify neural population discriminability based on distances in the response space between different stimuli or categories. In our data, we were also able to quantify and compare the discriminability or distance between stimuli based on these population representations. Such an approach, for example, allows one to quantify the effects of attention on these representations of

stimulus shape or location (Sereno & Lehky, 2018). Briefly, within the high-dimensional representation for the ventral stream (AIT), we find that shapes are more discriminable when directing attention to shape rather than directing attention to location.

We suggest that comparisons of stimulus categorization and discrimination at the population level, using high-dimensional representation spaces, would be helpful in distinguishing the functionality of different brain areas and help in connecting single-cell properties with functional behavior.

6. Intrinsic advantages: data-driven cross-stream comparison of shape and space encoding

In our own work in monkeys at a cellular or fMRI level, we report many *mixed* findings with shape selectivity in dorsal stream neurons (Figs. 4 and 5) (Peng et al., 2008; Sereno & Maunsell, 1998; Sereno et al., 2002) and retinal and eye position spatial selectivities in ventral stream neurons (Fig. 6) (Lehky et al., 2008; Sereno & Lehky, 2011a; Sereno et al., 2014). By using an intrinsic approach on the population data collected under identical conditions, we directly compared cortical representations in different processing streams. If the *mixed* properties were coming from projections or cross-talk from the other stream, we reasoned the representations in each stream should share some similarities. We were able to construct representations of stimulus shape (Lehky & Sereno, 2007) and space (Sereno & Lehky, 2011a; Sereno, Lehky, Patel, & Peng, 2010; Sereno et al., 2014) separately for both a late ventral cortical area and a dorsal area. Notably, these findings first demonstrated that these mixed properties (shape selectivities in dorsal; spatial selectivities in ventral) are prevalent and sufficient to recover a representation of shape and space in each stream (cortical area).

Secondly, and perhaps more significantly, using a data-driven, intrinsic approach we are able to show striking differences in the representations across streams, providing support for the idea that encodings, for both shape and space, are distinct and independent in these two cortical areas. First, with respect to representation of shape, despite robust shape selectivity at the cellular level in both ventral and dorsal cortical areas, we find that at a neuronal population representational level, the shapes are clustered and categorized according to visual similarity in a ventral stream area, whereas this is not the case for a population of shape selective neurons in a dorsal cortical area (Fig. 7). Given that we had tested only a small highly constrained set of 2D geometrical forms, it was difficult to determine exactly how this dorsal stream cortical area was organizing or encoding shape (the H-shape became an outlier). However, the findings demonstrate clear differences in the representation of shape between streams. The shape properties in the dorsal stream are distinct from those in the ventral stream and not a mere duplication of properties from the ventral stream. The shape features important for discriminating and categorizing objects for object recognition are likely not the same features that are important for dorsal stream functionality. Comparing monkey neurophysiological data in the ventral and dorsal streams under identical stimulus and task conditions, the categorization is substantially more prominent in the ventral population compared to the dorsal population data. We are not aware of

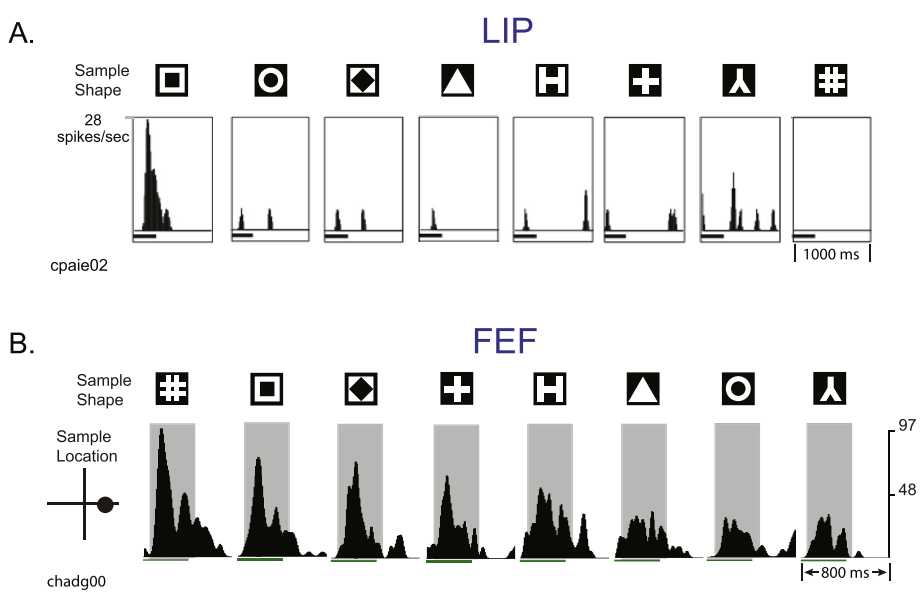

Fig. 4 – Example neurons in dorsal stream cortical areas with significant shape selectivity (*mixed* properties). A, Example neuron with narrow tuning from the lateral intraparietal cortex (LIP). B, Example neuron with broader tuning from the frontal eye field (FEF). The dark bar underneath the peristimulus time histograms indicates the stimulus durations during a passive fixation task. The shaded region shows the stimulus period, shifted by latency, during which average response rates were calculated for analyses. Figures adapted from Sereno and Maunsell (1998) and Peng et al. (2008).

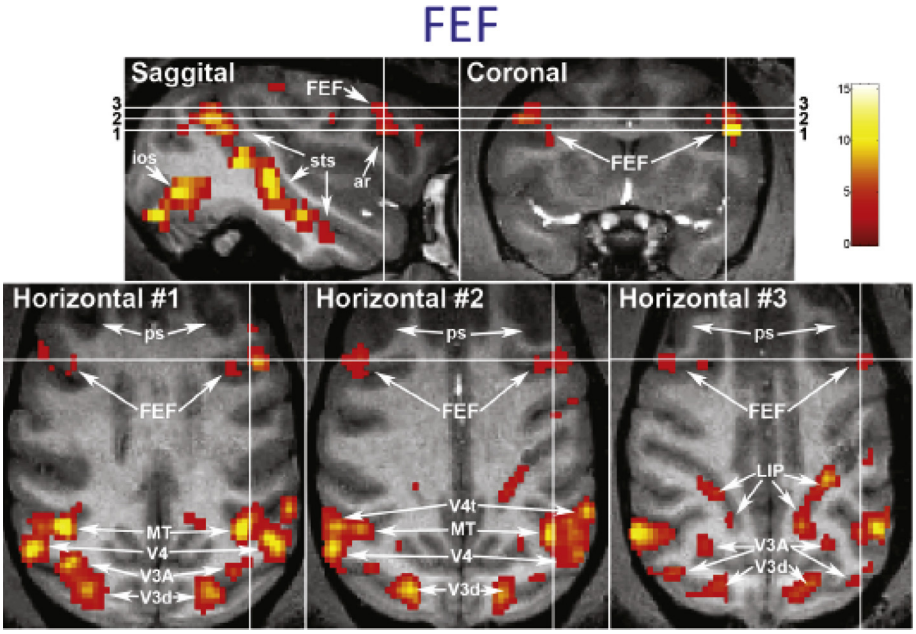

Fig. 5 – fMRI activation for 3D shape in a dorsal stream area – monkey frontal eye field (FEF). Significant activation for 3D versus 2D versions of surfaces defined by motion or contour. The white cross-hairs pinpoint activation in the FEF, on the anterior bank of the arcuate sulcus (ar), at the dorsal/ventral level of the principal sulcus (ps). Each white line specifies the position of one of the 2 other sections (e.g., the vertical line in the saggital section, which passes through the FEF, indicates the position of the coronal section). FEF activation is present in 3 contiguous 2 mm horizontal sections (labeled 1, 2, and 3). Other regions of activation shown include areas MT, V4, V3A, V3d, and LIP (the lateral intraparietal area). There is also activation in prefrontal cortex, extending down the sts (superior temporal sulcus) and in the ios (inferior occipital sulcus). The level of significance is indicated by the color bar, which shows *t*-score values. Figure adapted from Sereno et al. (2002).

similar comparisons of multiple brain areas using intrinsic population techniques with neurophysiological data.

Other fMRI work in humans has examined shape- and category-related representations in ventral and dorsal stream areas using MDS and RSA techniques (Bracci & Op de Beeck, 2016). The approach used is more extrinsic or model-driven than intrinsic because the predefined stimulus categories (each stimulus belongs to subcategories related to stimulus silhouette shape, semantic category, animacy, and action) and behavioral data serve as models for the analysis. The authors conclude that ventral stream areas preferentially represent object animacy while dorsal stream areas represent object action properties, although the data seem to show that ventral compared to dorsal stream regions have equal or greater correlations with both the animate/inanimate and action/non-action distinctions (see their Fig. 5). Nevertheless, the paper is one of a small set of studies that include an intrinsic analytic approach across visual streams.

Additional work investigating cross-stream and species (humans and monkeys) similarities and/or differences in shape representation have used fMRI adaptation to investigate object shape selectivity and size- and viewpoint-invariant shape responses (Kastner, Chen, Jeong, & Mruczek, 2017; Kastner, Pinsk, Arcaro, Li, & Konen, 2009). These studies found similar 2- and 3-D object shape selectivity in higher-level dorsal and ventral visual stream areas in humans and monkeys. This result in humans corroborated an earlier study (Konen & Kastner, 2008), while the findings in monkeys corroborated early electrophysiology (Sereno & Maunsell, 1998) and fMRI (Sereno et al., 2002) studies showing selectivity for 2- and 3-D shape in both temporal and parietal (e.g., in area LIP) cortex. In contrast, other early fMRI studies did not find shape selectivity in parietal cortex in humans (Kourtzi & Kanwisher, 2000) and monkeys (Vanduffel et al., 2002). In addition (Kastner et al., 2009, 2017), report similar size- and viewpoint-invariance in some higher level areas of the ventral and dorsal visual pathways in humans, and size- but not viewpoint invariance in parietal cortex of monkeys, hypothesizing that this difference between humans and monkeys in parietal cortex may be related to human-specific tool use behaviors. This work is notable in its use of cross-stream and species comparisons, an essential and effective approach often lacking in other studies.

Likewise, in our own work examining spatial representations, we find striking differences in retinotopic (Fig. 8) and eye position (Fig. 9) location space across streams, supporting the idea that spatial properties are also independently encoded in these two cortical areas. In particular, we find that at a neuronal population level, in a dorsal stream area, there is a very accurate and metric representation of location (*coordinate representation*), even when compared to the original physical locations of the target stimuli. In contrast, in a ventral stream area, there is a less accurate (more distorted) but nevertheless topologically correct representation of location (*categorical representation*). We argued that a coordinate representation, which is similar to the physical world,

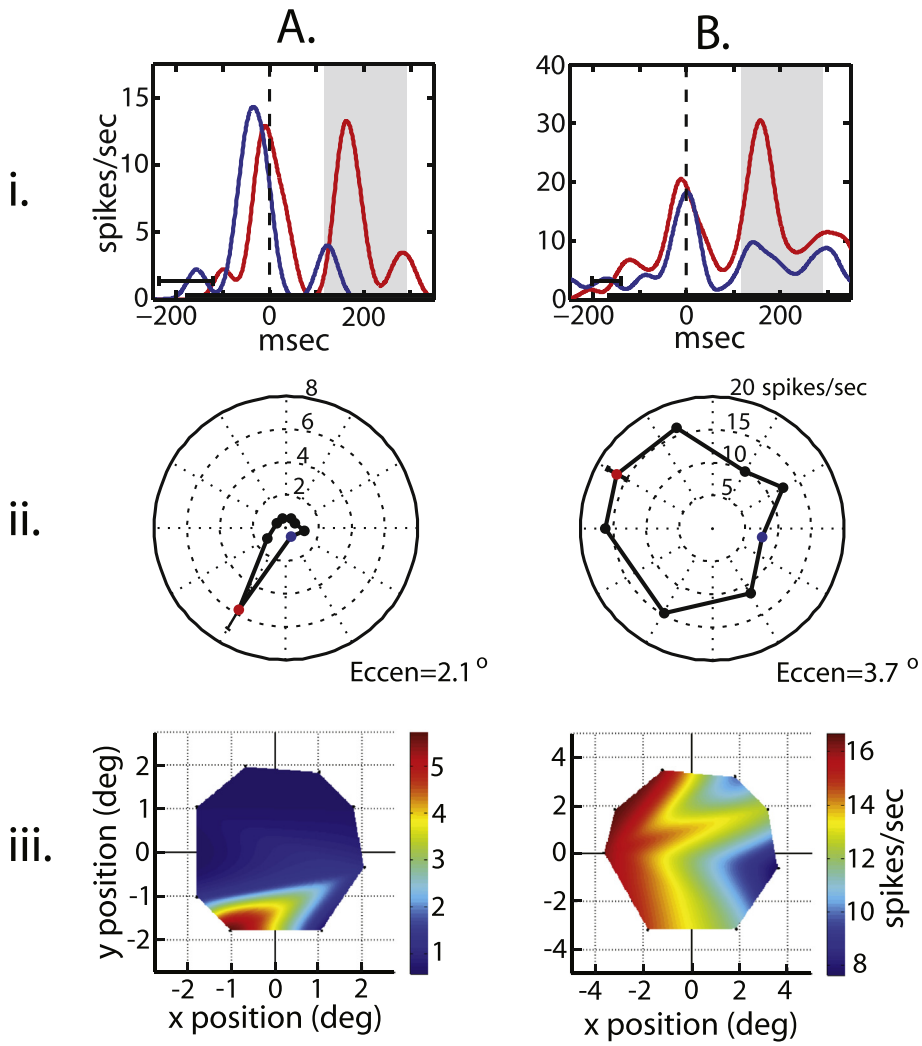

Fig. 6 – Example neurons in a ventral stream cortical area with significant spatial selectivity. Two example cells from anterior inferotemporal cortex (AIT) showing eye position effects: A, one neuron with narrow tuning; and B, one with broader tuning. *Row i*, Time course of responses at best (red) and worst (blue) eye positions. Gray period indicates target fixation period shifted by neural latency. Curves smoothed using a 20 msec Gaussian kernel. *Row ii*, Polar plots showing eye position effect. Radial dimension indicates firing rate, and angle dimension represents polar angle of stimulus position. Red and Blue dots indicate positions producing highest and lowest responses. *Row iii*, Interpolated response surface, showing firing rate as a function of eye position. Figure adapted from Lehky et al. (2008).

might be needed for dorsal stream cortical areas important for interacting with the world. In contrast, a categorical spatial representation might be sufficient for object and scene representation. That is, it may be important that a faucet is *above* the basin, in order for one to recognize an object as a sink (Fig. 10). However, if the faucet were placed *on the side of* the basin, the object may no longer look much like a sink. At the same time, exact or metric relationships may be less important for object and scene recognition. That is, whether the faucet was 6 or 12 inches above the basin, one could still easily recognize the object as a sink. Thus, a metric or accurate spatial representation important for interacting with the world (coordinate) may not be the optimal spatial representation needed for object and scene recognition (categorical).

7. Intrinsic modeling: elucidation of key physiological characteristics

By using an identical intrinsic approach with model neurons, we can explore and elucidate how single cell properties influence these population representations. Specifically, we can search for those key physiological characteristics that can explain the differences in encoding we see across cortical regions or instead identify invariances in these population representations (those changes in physiological properties that do not affect the encoding representation). We highlight here one example of a non-intuitive cognitive consequence derived from our neural population coding modeling of visual space (Lehky & Sereno, 2011; Sereno & Lehky, 2011). Receptive

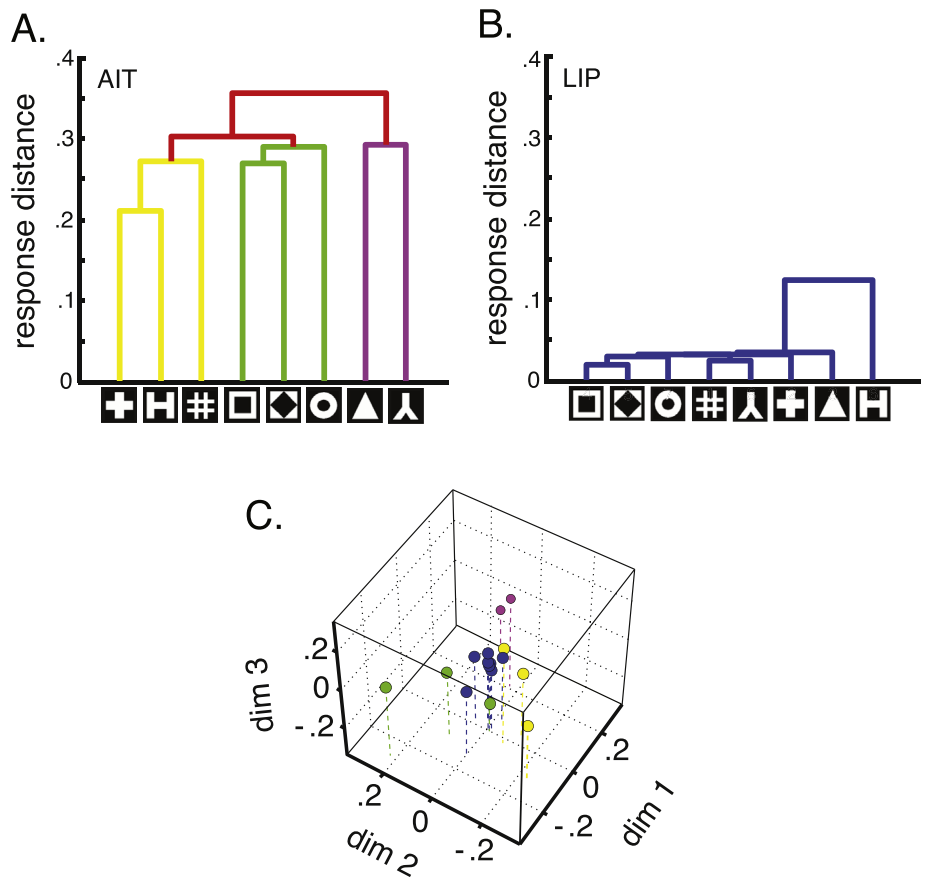

Fig. 7 – Intrinsic analyses and representation of shape encoding differences across streams. A, Cluster analysis dendrogram derived from the mean response distances of a population of shape selective anterior inferotemporal (AIT) neurons. Cluster analysis identified 3 groups of shapes (indicated by yellow, green, and pink), that could be characterized as shapes with horizontal and vertical features, doughnut-like shapes, and triangle-like shapes, respectively. B, Cluster analysis dendrogram derived from the mean response distances of a population of shape selective lateral intraparietal (LIP) neurons. Different shapes were less well separated than in AIT and did not show clear-cut clustering (with the exception of 1 outlier shape). C, Multidimensional scaling (MDS) analysis derived from mean response distances. Three-dimensional plot of neural shape space configurations for AIT and LIP. For AIT, points representing 8 shapes are color-coded into 3 groups, yellow, green, and pink, same coloring as in Fig. 7A (cluster analysis). The representation of shapes for LIP is indicated by blue points, clumped in a region near the origin because of the compressed scale of the LIP shape representation. Figure adapted from Lehky and Sereno (2007).

fields in inferotemporal cortex show selectivity to complex real-world objects compared to selectivity to simpler stimulus patterns observed earlier in the hierarchy of visual responsive cortical areas (Tanaka, 1996). Shape selectivity in inferotemporal neurons stays (approximately) invariant when the object stimulus shifts in size or when the stimulus shifts spatial location. In other words, inferotemporal neurons exhibit *spatial invariance* for size and translation (Desimone, Albright, Gross, & Bruce, 1984; Gross, Rocha-Miranda, & Bender, 1972; Ito, Tamura, Fujita, & Tanaka, 1995; Sawamura, Georgieva, Vogels, Vanduffel, & Orban, 2005; Tovée, Rolls, & Azzopardi, 1994). Associated with this spatial invariance in inferotemporal responses is the observation that receptive field diameters are larger than in earlier visual cortical areas within the ventral stream (Op de Beeck & Vogels, 2000). A widespread assumption is that the observed size and translation spatial invariance in inferotemporal responses is in some manner causally related to the large receptive field sizes in inferotemporal cortex.

However, the results of our intrinsic neural modeling (based on multidimensional scaling) show the opposite: having large receptive field diameters produce metrically accurate representations of physical space, whereas smaller receptive fields degrade the accuracy of spatial representations (Lehky & Sereno, 2011). In other words, the population modeling results indicated that large receptive fields are important for accurately localizing stimuli in space rather than creating spatial invariance through delocalizing stimulus responses. Although positional invariance of stimulus responses has long been associated with large receptive fields in object recognition models (e.g., Riesenhuber & Poggio, 2000; Serre et al., 2007), we find receptive field dispersion rather than receptive field

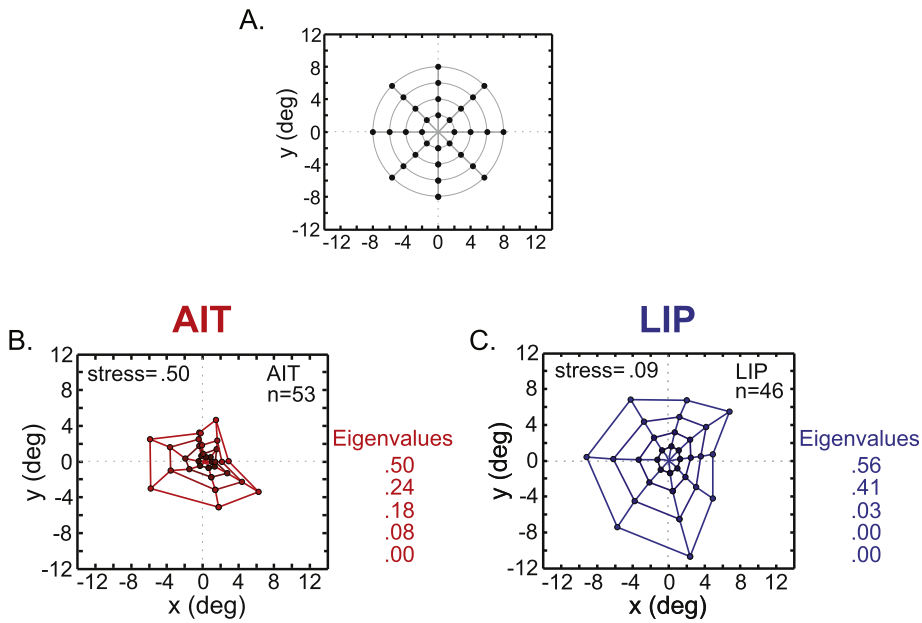

Fig. 8 – Intrinsic analyses and representation of spatial (retinal) encoding differences across streams. MDS analysis was performed on neurons that had significant retinal spatial selectivity. *A*, Black dots indicate the set of physical (retinal) stimulus positions used as input for the MDS analysis. Lines connecting the positions merely help illustrate iso-eccentricity positions and iso-polar angles as well as highlight the overall symmetry of the spatial configuration. *B*, Configuration of spatial locations recovered from AIT data, shown in red. Coloring becomes darker for points closer to the origin, to aid visualization. Normalized eigenvalues are displayed. *C*, Configuration of spatial locations recovered from LIP data, shown in blue. Presentation details are the same as in panel B. The LIP stress value is lower than in AIT, indicating a more veridical representation of physical space. Figure adapted from Sereno and Lehky (2011a).

diameter to be the critical parameter (Lehky & Sereno, 2011; Sereno & Lehky, 2011b). Receptive field dispersion indicates how broadly receptive field centers are spread out from the fovea. In fact, our modeling suggested that higher ventral stream areas with highly restricted receptive field dispersion would be unable to achieve positionally invariant population representations beyond this narrow region around fixation. The importance of receptive field dispersion for spatial representations at the population level had not been realized based on single-cell neurophysiology. Counterintuitive modeling results showing more accurate spatial representations with large receptive fields, as well as showing the importance of the population dispersion of receptive fields, have practical implications when decoding population activity, for example for brain computer interfacing for neural prosthetics.

8. Effects of attention on population representations across cortical streams

Neurophysiological effects of attention appear to be ubiquitous in both the ventral and dorsal visual streams (Chelazzi, Della Libera, Sani, & Santandrea, 2011; Colby & Goldberg, 1999; Desimone & Duncan, 1995; Maunsell, 2015; Reynolds & Chelazzi, 2004). In the ventral stream, this includes attentional effects in V4 (McAdams & Maunsell, 1999; Moran & Desimone, 1985; Nandy, Nassi, & Reynolds, 2017) as well as inferotemporal cortex (e.g., Chelazzi, Duncan, Miller, & Desimone, 1998; Zhang et al., 2011). In the dorsal stream, attentional effects are prominent in MT and MST (Martínez-Trujillo & Treue, 2002; Treue & Maunsell, 1996), as well as LIP (Bisley & Goldberg, 2003; Colby et al., 1996), among other cortical areas. Initially the neurophysiological data concentrated on attentional effects on stimuli location (Colby et al., 1996; Desimone, 1998; McAdams & Maunsell, 1999; Moran & Desimone, 1985; Treue & Maunsell, 1996), suggesting that attention was primarily a spatial phenomenon. However, it is now well established that attention to feature or shape also modulates stimulus response (Maunsell & Treue, 2006; McAdams & Maunsell, 2000; Treue & Martinez-Trujillo, 1999).

Neurophysiological studies in the past have focused on attentional effects at the single-cell level rather than at the population level. That is to say, the neurophysiological studies have concentrated on how, for example, attention affects the average response of individual cells in a given cortical area as a function of some stimulus parameter (e.g., McAdams & Maunsell, 1999; Treue & Maunsell, 1996) or perhaps how attention affects the correlation of pairs of neurons (e.g., Cohen & Maunsell, 2009; Mitchell, Sundberg, & Reynolds, 2009). Absent are studies of how attention affects population activity as a whole within high-dimensional representations of stimuli.

In addition to neglecting the effects of attention at the population level, previous neurophysiological studies have not investigated how population coding of attention differs between cortical areas in the two visual streams under

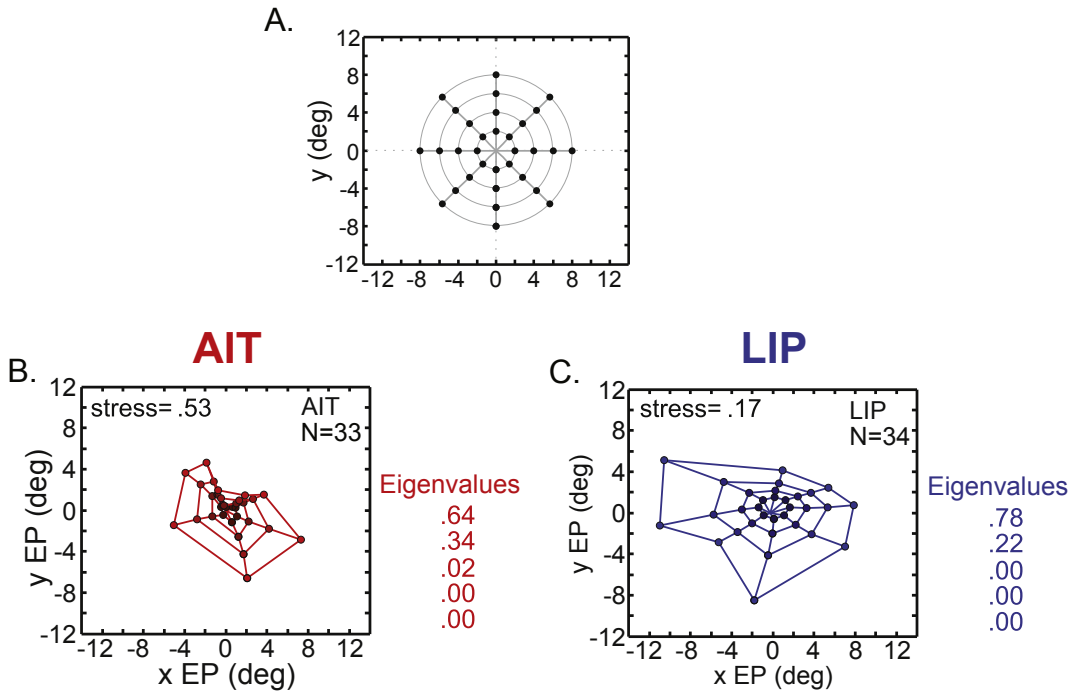

Fig. 9 – Intrinsic analyses and representation of spatial (eye positions) encoding differences across streams. MDS analysis was performed on neurons that had significant eye position (gaze angle) spatial selectivity. *A*, Black dots indicate the set of eye positions (gaze angle) used as input for the MDS analysis. Lines connecting the positions merely help illustrate iso-eccentricity positions and iso-polar angles as well as highlight the overall symmetry of the spatial configuration. *B*, Configuration of eye positions recovered from AIT data, shown in red. Coloring becomes darker for points closer to the origin, to aid visualization. Normalized eigenvalues are displayed. *C*, Configuration of spatial locations recovered from LIP. Presentation details are the same as in panel B. There is less distortion apparent in the spatial layout of the LIP grid compared to AIT and the LIP stress value is lower than in AIT, indicating a more accurate recovery of eye positions. Figure adapted from Sereno et al. (2014).

identical experimental conditions. Although there are a small number of physiological studies examining attention in different cortical areas using identical stimuli (Arcizet, Mirpour, Foster, & Bisley, 2018; Bichot, Heard, DeGennaro, & Desimone, 2015; Zhou & Desimone, 2011), these studies were conducted at the single-cell level and not the population coding level (representational level).

We recently extended our work on population coding of visual parameters by using an intrinsic approach to examine how attention modulates the representation spaces for stimulus shape and retinotopic location in ventral and dorsal streams (Fig. 11) (Sereno & Lehky, 2018). We find significant attentional modulation of single-cell responses in cortical areas for both streams (Fig. 12), as has been reported in previous reports of single-cell results described above. However, our data evaluated at the population level using multidimensional scaling did not show significant attentional effects in LIP, although at the population level there are significant attentional effects in AIT. That is to say, attention alters the population representation of both shape and space more strongly in ventral stream than in dorsal stream.

In particular, when an animal attends to an object's shape we find greater response distances (discriminability) within the neural representation space between the shapes (Fig. 13) and, surprisingly, also improved spatial discriminability of target locations in ventral stream representations compared to changes (or lack of changes) in the dorsal stream (Fig. 14). Although one might expect attention to shape to increase discriminability (distances in the neural population representation) between shapes in a ventral stream cortical area, it is less clear that it should enhance *spatial* discrimination. We argued that subtle shifts in spatial relationships might be key in object and scene recognition in order to discriminate consequential category distinctions (e.g., whether a window is open or closed, locked or unlocked). In addition to these increases in discriminability for shape and space, we also find non-linear distortions or warping of the shape and location representations in ventral stream (Fig. 15). Thus, it appears that the representations for both shape and space in ventral stream are flexible and dependent on attention, context, and/or task demands whereas the representations in dorsal stream remain to some degree impenetrable to these conditions (Figs. 13B and 14B), despite equal or greater modulations occurring at the single-cell level (see Fig. 12B). It is possible that ventral stream plays a role in cognitive operations that must be able to rapidly adapt and adjust to changing attentional and task conditions, whereas dorsal stream, although responsive to these rapidly changing conditions at a cellular

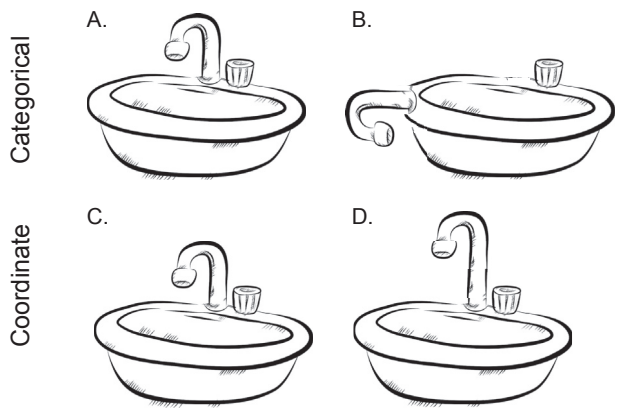

Fig. 10 – Categorical (ventral stream) versus coordinate (dorsal stream) spatial relations. *A*, Topologically proper categorical relation between the faucet and basin, namely, the faucet is above the basin. The object is easily recognized as a sink. *B*, Topologically improper categorical relation between the faucet and basin, namely, the faucet is on the side of the basin. The object is *not* easily recognized as a sink. *C-D* Example variant coordinate spatial relations between the faucet and basin, namely, the faucet is either 6 inches (in *C*) or 12 inches (in *D*) above the basin. Although clearly different objects, both objects can be easily recognized as a sink. We find striking differences in location space across ventral and dorsal streams and argued that an accurate and metric (coordinate) representation, which was similar to the physical world, might be needed for dorsal stream cortical areas important for interacting with the world (e.g., accurately placing your hands under the faucet to wash them). In contrast, we argued that a relative or topological (categorical) spatial representation might be sufficient for object and scene recognition in the ventral stream.

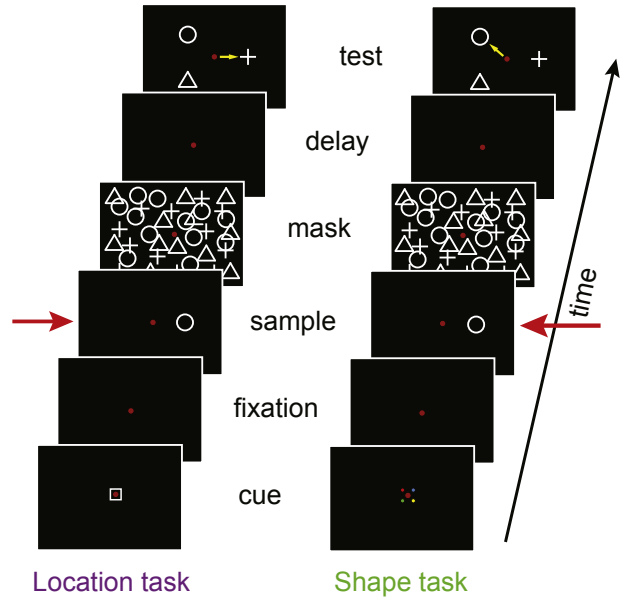

Fig. 11 – Attention task sequence. A cue at the start of a trial indicated to the monkey which of two attention tasks to perform, either a shape attention task or a location attention task. Following the cue a sample stimulus was presented, which consisted of a single shape presented at a particular location. Following a delay period the test stimulus was presented, which consisted of three shapes presented at three locations. For the location attention task the monkey made a saccade to the location matching the location of the sample stimulus, ignoring shape. For the shape attention task, the monkey made a saccade to the test shape matching the sample shape, ignoring location. The red arrows indicate the stimulus period, shifted by latency, during which average response rates were calculated for attentional analyses. Figure adapted from Sereno and Lehky (2018).

level, must maintain a constant (veridical) representation of shape and space in order to facilitate interactions with the world.

9. Future directions: intrinsic modeling of attention

In order to better understand these attentional differences (i.e., population coding differences at a representational level due to an attention manipulation), and more specifically, the effects of various cellular attentional modulations on the response distance or discriminability of stimulus items in a high-dimensional neural representation, a model with synthetic responses based on prior physiological data would be helpful. In our own work, we have previously had much success applying MDS to systems level modeling (Lehky & Sereno, 2011; Lehky, Sereno, & Sereno, 2016). There are a wide variety of attentional phenomena reported in the experimental literature [for recent review, see Sereno and Lehky (2018)] that may also be amenable to modeling within our population response space approach. For example, at a single cell level, much work suggests that attention modulates the gain of neural responses to a stimulus in the receptive field (Colby et al., 1996; Martínez-Trujillo & Treue, 2002; McAdams & Maunsell, 1999, 2000; Reynolds, Pasternak, & Desimone, 2000; Treue & Martinez-Trujillo, 1999; Williford & Maunsell, 2006). In addition, attention has also been shown to change the statistics of stimulus responses (Bichot, Rossi, & Desimone, 2005; Cohen & Maunsell, 2009, 2011; Fries, Reynolds, Rorie, & Desimone, 2001; Fries, Womelsdorf, Oostenveld, & Desimone, 2008; Lakatos, Karmos, Mehta, Ulbert, & Schroeder, 2008; Mitchell et al., 2007, 2009; Wróbel, 2014), including their variance. Consideration and testing of such observations through modeling of high-dimensional population response vectors may lead to insights concerning attentional processing. Likewise, the feature-similarity gain model of Martinez-Trujillo and Treue (2004), an extrinsic model which proposes a multiplicative modulation based on both the attended feature and the cell's preferred feature, may gain from a novel perspective if recast using a framework based on population response vectors rather than summary statistics of a population distribution, as is currently being done. Although the feature-similarity gain model, similar to other attentional models, examines a relatively simple 1D

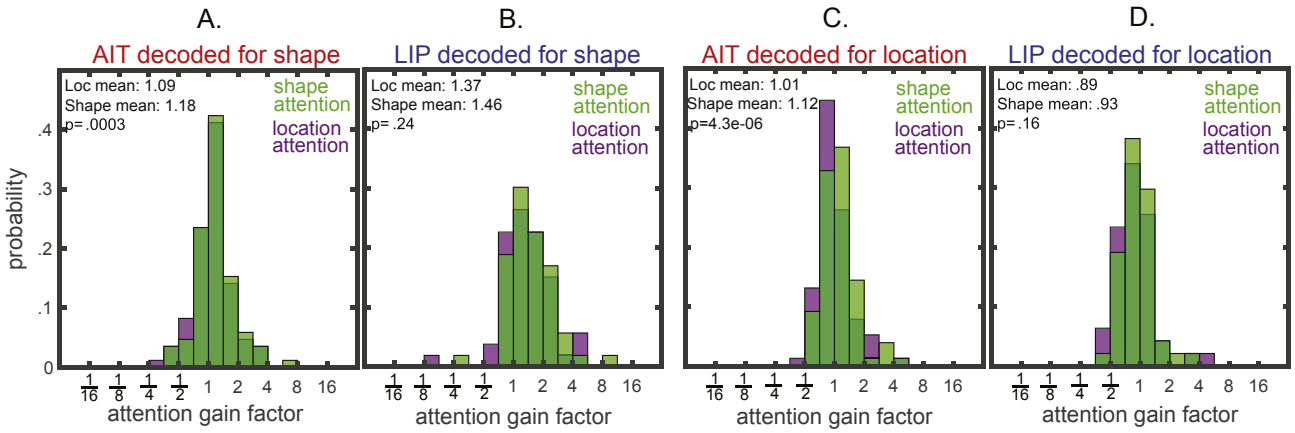

Fig. 12 – Attentional gain factors associated with the two attention tasks (shape attention task and location attention task). *A-B*, Attentional gain factors of AIT and LIP neurons when neural responses were decoded for stimulus shape. Gains for the two attention tasks (attention to shape in green and location in purple) were measured relative to neural activities during a passive shape task. *C-D*, Attentional gain factors of AIT and LIP neurons when neural responses were decoded for stimulus location. Gains for the two attention tasks (attention to shape in green and location in purple) were measured relative to neural activities during a passive location task. Significance of the difference between attention tasks was calculated using the Wilcoxon signed rank test. Figure adapted from Sereno and Lehky (2018).

feature space (motion direction), future models of attentional processing, based on intrinsic population coding methods, may be able to be extended to a multidimensional feature space, such as a feature space for shape [see Grunewald and Skoumbourdis (2004) for an example of a 2D feature space, integrating motion and disparity]. It would remain an empirical question for future intrinsic modeling studies to determine whether feature-similarity changes in neural population response vectors could account for the attentional effects and/or differences we find at a representational level in ventral and dorsal streams.

Hence, using a population of neurons modeled on recorded neurons that, for example, manipulated the gain, variance, or feature-similarity gain of these model neurons could provide insight into how these aspects of neuronal response might influence the representations of shape and location at the population level. Such modeling will be critical to better understand how seemingly similar attentional gain distributions in populations of ventral and dorsal stream neurons can lead to such striking differences at the representational level, with attention to shape modulating both the representation of shape and location space in ventral stream while hardly

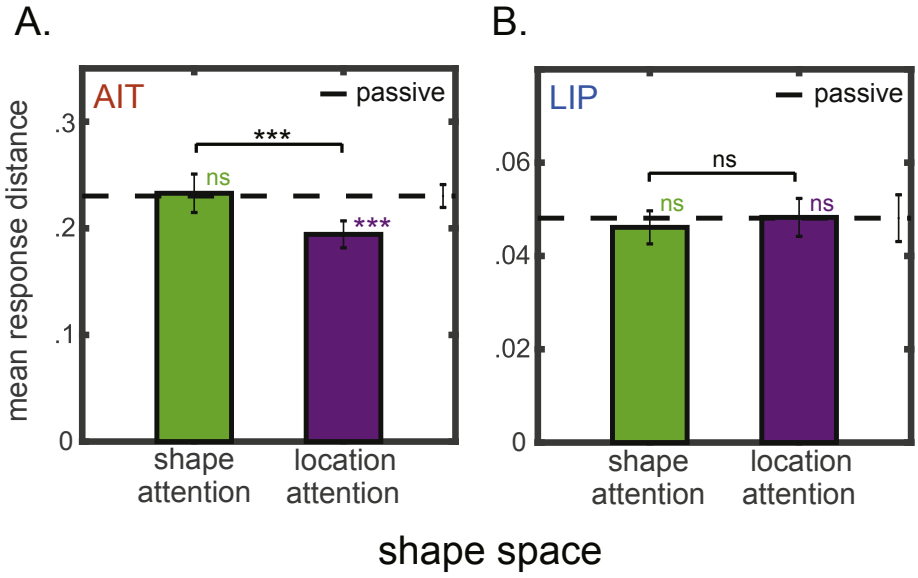

Fig. 13 – Attention to shape increases mean response *distance between shapes* in *A*, area AIT but not in *B*, LIP (mean distance between neural population response vectors for shape are pooled over all stimulus shapes in a cortical area). The dashed lines indicate the response distances under the passive shape task. Asterisks indicate statistically significant differences under the Wilcoxon rank sum test. Error bars indicate standard error. Figure adapted from Sereno and Lehky (2018).

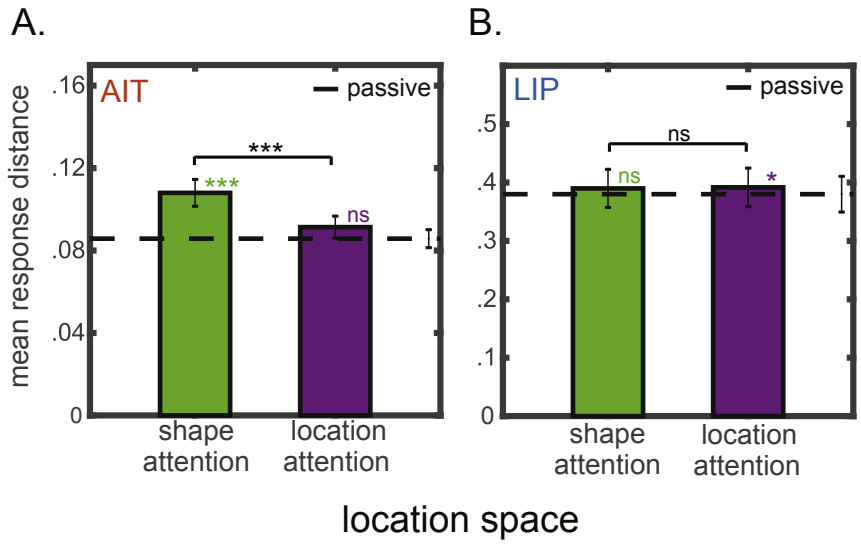

Fig. 14 – Attention to shape increases mean response *distance between locations* in *A*, area AIT but not in *B*, LIP (mean distance between neural population response vectors for location are pooled over all stimulus locations in a cortical area). The dashed lines indicate the response distances under the passive location task. Asterisks indicate statistically significant differences under the Wilcoxon rank sum test. Error bars indicate standard error. Figure adapted from Sereno and Lehky (2018).

changing shape and location representations in dorsal stream. Understanding what neuronal properties lead to attentional differences at the representational level is an important first step toward any larger goals or hopes of future intervention in human diseases.

10. Summary and implications

Despite a wealth of knowledge about single-cell response for shape, space, and attention across many brain regions, little is understood about how these properties relate to differences in population representations across cortical regions, important for behavior and intervention in human disease. Recent work has blurred distinctions between properties in the 'what' (ventral) and 'where' (dorsal) cortical visual streams, with findings demonstrating single-cell shape, space, and attention effects in many cortical areas in both streams. We show here that a data-driven intrinsic approach to population coding can (1) provide insight into differences in population representations across cortical regions, including differences in categorization and discrimination and differences in the representation of shape, space, and attention; as well as (2) help to identify key receptive field properties crucial in either localizing a target or allowing position invariance.

Briefly, we show how intrinsic population approaches, such as MDS, are data driven and can provide an explicit measure of categorization and discrimination (because they make explicit the geometrical relationships among different stimuli within the high-dimensional neural representation space). In contrast, in extrinsic analysis, there is no innate basis for categorization or discrimination, and analysis proceeds by constructing a specific statistical model followed by painstaking hypothesis testing. Using intrinsic population coding approaches, we show that shape information in the ventral stream is qualitatively different from shape information in the dorsal stream (Lehky & Sereno, 2007), suggesting that shape representations are generated independently within the two streams and not through cross-talk between them. This differs from Kastner and colleagues' conclusions (Kastner et al., 2009, 2017; Konen & Kastner, 2008) that object information, at least with respect to shape and size invariance in monkeys, may be represented similarly in ventral and dorsal streams. Further understanding of the shape representation space in both streams would benefit from being re-examined using an intrinsic approach with a larger sample of well-controlled shapes. Similarly, we find that spatial information in the two streams are also qualitatively different (Sereno & Lehky, 2011a; Sereno et al., 2014), again suggesting that spatial information in the two streams are independent and not generated merely through cross-talk.

Further, our intrinsic population modeling results indicate that large receptive fields are important for accurately localizing stimuli in space rather than creating spatial invariance, as has been often argued (Booth & Rolls, 1998; Desimone & Gross, 1979; Gross et al., 1972; Ito et al., 1995) and even implemented in object recognition models (e.g., Riesenhuber & Poggio, 2000; Serre et al., 2007). Intrinsic modeling further identifies receptive field dispersion (i.e., how broadly receptive field centers are spread out from the fovea) rather than receptive field diameter as the critical parameter that results in position invariance or localization accuracy and predicts that higher ventral stream areas with highly restricted dispersion would be unable to achieve positionally-invariant population representations

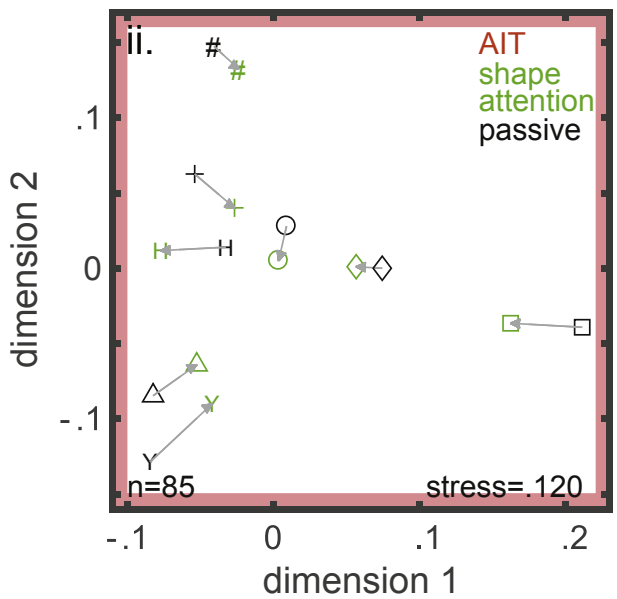

Fig. 15 – MDS shape space compared during shape attention task versus passive shape task, showing nonlinear effects. In both cases the Procrustes transform including scaling was applied to remove linear effects of attention on the shape maps, leaving nonlinear (non-uniform) effects. Arrows link corresponding points in the two shape spaces and show that attention causes come shape response distances to increase and other shape response distances to decrease. Attentional differences ($p < .05$) between scaled shape spaces were examined by bootstrap resampling. This comparison was significant and indicated that, in addition to the increased mean shape response difference in ventral stream (see Fig. 13A), there was also a significant nonlinear distortion or warping of the multidimensional shape representation space. Figure adapted from Sereno and Lehky (2018).

beyond this narrow region around fixation. We are unaware of any prior claim that has suggested that receptive field dispersion found in single-cell recordings is important for determining the population spatial representations.

Perhaps most importantly, we show how intrinsic analytic approaches, such as MDS, can elucidate cross-stream comparisons and clarify representational differences. Whereas recent single-cell findings appear to blur the usual what/where distinctions and result in a mixing or amalgamation of shape and space parameters in cortical areas, we show how an intrinsic population approach allows us under identical conditions to directly compare how shape and space are represented in each pathway and how attention might influence those representations. This allows us to step beyond the single-cell, simplified view of segregation of properties. More importantly, it reveals striking differences between ventral and dorsal streams in the representation of shape, space, and attention that are not apparent at a single-cell level. With respect to attention, we suggest that the representations for both shape and space in ventral stream are flexible and dependent on attention, context, and/or task demands whereas the representations in dorsal stream remain to some degree impenetrable to these conditions. Our findings that ventral stream representations are flexible are partially in agreement with a recent imaging study in humans using a multivariate analysis of fMRI data. In this study, Çukur et al. (2013) demonstrated that attention can cause a shift or warping of semantic representations in ventral stream. However, unlike our findings, they showed warping in dorsal stream areas as well. In addition to differences in technique (imaging *vs* physiology), there were a number of differences in stimuli, tasks, and methods that perhaps engendered differences between studies. Although our initial findings and novel application of intrinsic population approaches for cross-stream comparisons are stimulating, additional carefully controlled, cross-stream comparisons of population representations are needed to further expose the crucial differences in processing across brain regions.

While we have emphasized neurophysiology data when discussing intrinsic population methods, such intrinsic methods are also applicable to fMRI data, as was mentioned earlier. Both types of data have their advantages and weak points. In particular, fMRI has an advantage over neurophysiology in being able to cover a lot of cortical regions quickly and efficiently. On the other hand, a single voxel in fMRI will pool on the order of 100,000 neurons (Aguirre, 2012). Possibly population decoding techniques using fMRI data may be more applicable to situations where neurons with similar functional properties tend to cluster within individual voxels (Dubois, de Berker, & Tsao, 2015).

11. Conclusion

Although much has been learned about the detailed response properties at the single-cell level of many regions of the brain, a deeper understanding of how these properties collectively lead to different functions at the population level in various cortical regions and how they relate to behaviors such as attention remains elusive. Without a clearer understanding of behaviors such as attention, current interventions remain rather haphazard, and optimal interventions in human disease stay a distant goal. In order to accelerate the translation of our understanding of changes at the cellular level into better understanding of the function and interaction of different brain regions, we must have a better understanding of how these properties are being encoded at the population level in these different brain regions. We demonstrate that intrinsic approaches offer insight into how neuronal populations differ in the encoding of shape and space, and offer insight into how attention is differentially influencing these representations in different cortical regions. Application of these same intrinsic approaches to neuromodeling provides a tool to explore how the different cellular characteristics can or cannot help explain cortical differences in representations as well as help identify and limit the critical variables physiologists need to focus on and measure. Using an intrinsic approach has provided insight into the cortical representation of shape, space, and attention and we expect that such

understandings and novel approaches will eventually lead to more successful interventions and treatments in human disease.

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