

In Sync

Citation for published version (APA):

Karimian, M. (2022). *In Sync: Neural Oscillations and their Relation to Visual Perception and Learning*. [Doctoral Thesis, Maastricht University]. Maastricht University. <https://doi.org/10.26481/dis.20221031mk>

Document status and date:

Published: 01/01/2022

DOI:

[10.26481/dis.20221031mk](https://doi.org/10.26481/dis.20221031mk)

Document Version:

Publisher's PDF, also known as Version of record

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

[Link to publication](#)

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license above, please follow below link for the End User Agreement:

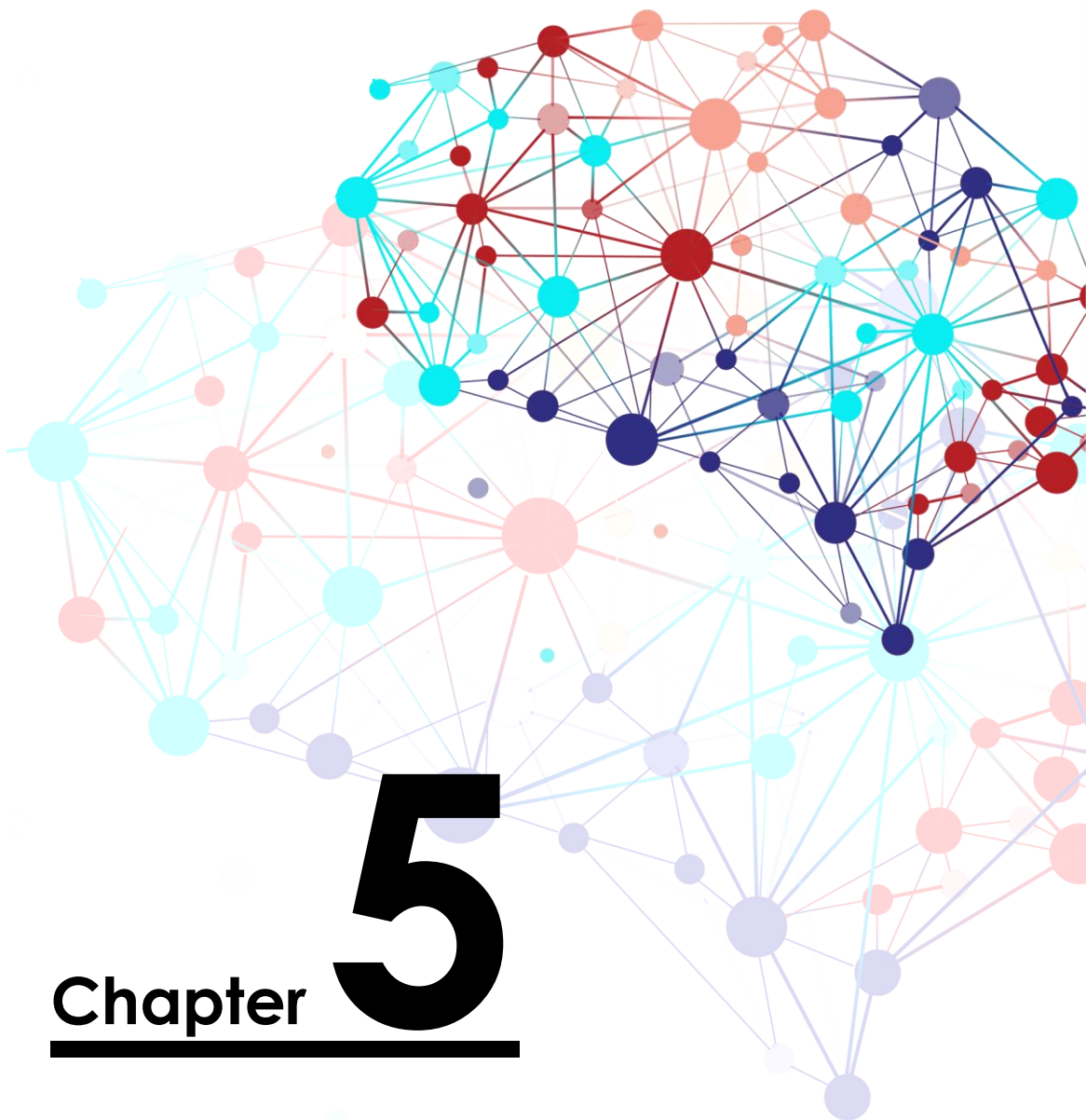
www.umlib.nl/taverne-license

Take down policy

If you believe that this document breaches copyright please contact us at:

repository@maastrichtuniversity.nl

providing details and we will investigate your claim.



Chapter **5**

General summary and Discussion

5-1. Aims of the thesis

Neural oscillators and their synchronization take centre stage in the present thesis with an emphasis on the role of gamma synchronization in cortical information processing. While stimulus-induced cortical oscillations in the gamma range are ubiquitous in the cortex (Bertrand & Tallon-Baudry, 2000; N. Brunet et al., 2015; Buzsáki & Wang, 2012), a number of studies have cast doubt on the notion that they play a functional role. In particular, critiques that long signal propagation delays (Ray & Maunsell, 2015) and high variance among frequencies in the gamma range (D. Hermes, Miller, Wandell, & Winawer, 2015; Jia, Xing, & Kohn, 2013; Ray & Maunsell, 2015) may interfere with synchrony-based neural information processing have been influential. Prior neurophysiological studies have shown however that neither propagation delays (Fries, Nikolić, & Singer, 2007; Nikolić, 2006) nor frequency variance (Fries et al., 2007; Lowet, Roberts, Peter, Gips, & de Weerd, 2017) are necessarily detrimental to the selective and flexible synchronization required for neural information processing. According to the theory of weakly coupled oscillators (TWCO), the distribution of intrinsic frequencies differences (frequency detuning) among oscillators as well as the strength of their interactions (coupling strength) determines the likelihood that oscillators synchronize (Pikovsky, Rosenblum, Self, & 2001, 2003). In other words, a frequency difference can still permit (partial) synchronization when there is sufficient coupling strength. The existence of long propagation delays and associated variability when communicating oscillators are at various distances from each other in a network can affect synchronization. Nevertheless, empirical evidence indicates that within a range, variable propagation delays do not render synchronization impossible (Fries et al., 2007; Nikolić, 2006). Thus, rather than considering the existence of variability in propagation delays among remote oscillators as an absolute argument against synchronization as a viable mechanism for information processing, it may be considered as a factor that can be used by the brain to control synchronization. Variability in propagation delays may exert their effect by affecting detuning (Buia & Tiesinga, 2006; Fries, 2005). Hence, TWCO posits that coupling strength and frequency detuning are crucial factors controlling synchronization behaviour among oscillators. Using this framework, and in order to investigate the usefulness of gamma synchronization in (visual) information processing, we aimed to address the following questions:

- 1) What are the effects of (plastic) coupling delays on the synchronization behaviour and synaptic plasticity within a phase oscillator network and how does this affect structural and functional features of the network (Chapter 2)?

- 2) To what extent is a phase oscillator network exposed to texture stimuli capable of predicting human figure-ground segregation performance (Chapter 3)?
- 3) To what extent are learning-induced structural changes in a phase oscillator network exposed to texture stimuli predictive of human performance improvement on a figure-ground segregation task (Chapter 4)?

5-2. Summary of Results

Before presenting a detailed summary of results per chapter addressing the above-formulated aims, the main results are briefly summarized here. The results in Chapter 2 demonstrate that signal propagation delays and experience-induced plasticity affect the (spatial) distribution of gamma frequencies in a network of oscillators (Buia & Tiesinga, 2006; Fries, 2005) as well as the strength of coupling among neural oscillators. Thus, propagation delays vary as a function of distance, but are at the same time subject to plastic regulatory mechanisms that use propagation delays as a tool to facilitate or prevent synchronization between different groups of oscillators. The results in Chapters 3 and 4 support the perceptual relevance of levels of synchronization as controlled by detuning and coupling strength in an oscillator network (Baldi & Meir, 1990; Buia & Tiesinga, 2006; Dubey & Ray, 2020; Feng, Havenith, Wang, Singer, & Nikolić, 2010; Gieselmann & Thiele, 2008; Gilbert & Wiesel, 1983; Gray, König, Engel, & Singer, 1989; Hadjipapas, Lowet, Roberts, Peter, & de Weerd, 2015; Hall et al., 2005; Henrie & Shapley, 2005; Logothetis, Pauls, Augath, Trinath, & Oeltermann, 2001; Lowet et al., 2015, 2017; Ray & Maunsell, 2010; Roberts et al., 2013; Shapira et al., 2017; Stettler, Das, Bennett, & Gilbert, 2002; Swettenham, Muthukumaraswamy, & Singh, 2009; Ts'o, Gilbert, & Wiesel, 1986; M. A. Whittington, Traub, Kopell, Ermentrout, & Buhl, 2000; Miles A. Whittington, Cunningham, LeBeau, Racca, & Traub, 2011). We found an excellent fit between model predictions of synchronization levels associated with manipulations of stimulus- and experience-dependent factors on the one hand, and behavioural measures of human figure-ground segregation on the other. Hence, the present thesis has contributed behavioural and computational modelling research that argues against the idea that (because of detuning and because of the long transmission delays in long-range communication) gamma oscillations would be useless epiphenomena of visual processing without a substantial contribution to visual perception and other forms of cognition.

5-2-1. Chapter 2: Effects of Plastic Coupling delays and Plastic Coupling Strengths on the Synchronization and Learning in Networks of Coupled Oscillators

Chapter 2 addressed the question how (plastic) coupling delays affect synchronization behaviour and synaptic plasticity in a phase oscillator network. In this chapter, synchronization was investigated in a ring network of coupled phase oscillators whose pairwise coupling strength and conduction velocities were plastic. What is presented in this chapter is a simple neural mass model developed to evaluate structural (pairwise connection strength and conduction velocity) and functional states (local and global synchronization behaviour) of a one-dimensional network of self-sustained oscillators that receives no external input. The network's states evolved based on the activity-dependent interplay between synaptic plasticity (connectivity strength) and myelin plasticity (conduction velocity). Synaptic plasticity was implemented in terms of activity-dependent modifications of pairwise connection strengths, whereas myelin plasticity was implemented indirectly through its effects on axonal conduction velocities and therefore signal transmission delays.

The contributions of synaptic plasticity to various forms of learning and memory have been extensively studied (Milner, Squire, & Kandel, 1998; Niyogi & English, 2009; Nowotny, Zhigulin, Selverston, Abarbanel, & Rabinovich, 2003; Seliger, Young, & Tsimring, 2002; Siri, Quoy, Delord, Cessac, & Berry, 2007; Song, Miller, & Abbott, 2000; Timms & English, 2014; Traubab et al., 1998), whereas the contribution of myelin plasticity to learning has become recognized only more recently as an important mechanism for learning and memory (Nickel & Gu, 2018; Sampaio-Baptista et al., 2013; Scholz, Klein, Behrens, & Johansen-Berg, 2009). Studies of the mechanisms of myelination (Fields, 2015; Fields & Bukalo, 2020; Giedd et al., 1996; Pajevic, Basser, & Fields, 2014; R. D. Fields, 2014) combined with diffusion neuroimaging studies of plastic changes in the integrity of white matter (Chang, Redmond, & Chan, 2016; Dutta et al., 2018; Fields, 2015; McKenzie et al., 2014; Pajevic et al., 2014; Purger, Gibson, & Monje, 2016; Scholz et al., 2009) indicate that myelination remains plastic throughout life (Giedd et al., 1996). Moreover, myelin plasticity depends, like synaptic plasticity, on the temporal relations of spiking activity between pre- and post-synaptic neural populations (Fields, 2015; Pajevic et al., 2014; R. D. Fields, 2014). Accordingly, synaptic and myelin plasticity in our model were both governed by Hebbian learning rules. The effects of both kinds of plasticity were assessed in terms of functional connectivity (synchronization behavior) in the model network and in terms of structural connectivity (myelination of axons and synaptic connectivity strength). The resulting

model revealed significant differences in both structural and functional connectivity when separately considering effects from pure synaptic plasticity, from pure myelin plasticity and from the interplay between the two. For example, with respect to synaptic plasticity, we found that for conditions in which the phase oscillator network developed two segregated structural clusters, also two corresponding, segregated, functional clusters emerged. In other words, parts of the network where the oscillators became more weakly connected also showed less synchronization. However, when in the same conditions that led to a segregation of the network into two separate clusters, myelin plasticity was allowed, this resulted in the formation of a single functional cluster. In other words, functional integration (synchronization) occurred across structurally segregated clusters. Because in this chapter we only studied the internal dynamics of the constructed network, without external input, an interpretation of these findings at the level of perception and cognition is difficult. Nevertheless, the fact that a larger network can be segregated into subnetworks is conceptually important for understanding perception and cognition. Note however that the model used in Chapter 2 does not relate to specific spatial and temporal scales. Instead, it provides a general framework to study neural oscillatory networks at any spatio-temporal scale.

5-2-2. Chapter 3: Role of the Synchronization among Stimulus-dependent Gamma Oscillations in Figure-ground Segregation

The third chapter asked the question whether gamma synchronization assists in figure-ground segregation. To address this question, we first designed a network of coupled phase oscillators exposed to texture stimuli. The oscillator network was designed to reflect elementary V1-like neural circuits. For this reason, dynamical and structural network parameters were based on electrophysiological recordings and organizational principles of V1 in macaques (Lowet et al., 2017) and humans (Balasubramanian & Schwartz, 2002; Polimeni et al., 2005; Schwartz, 1980). The scope of this chapter's main question was limited to an investigation of whether synchronization could constitute a pre-attentive process in early visual areas that supports figure-ground segregation in texture stimuli.

The texture stimuli comprised Gabor annuli arranged on a random grid. Each stimulus included a rectangular region, the figure, where annulus contrast was less heterogeneous than in the background. Based on prior observations in early visual cortex that local contrast drives gamma frequency (Hadjipapas et al., 2015; Henrie & Shapley, 2005; Lowet et al., 2015; Roberts et al., 2013; Shapira et al., 2017) and that coupling strength depends on cortical distance (Gilbert & Wiesel, 1983; Lowet

et al., 2015, 2017; Stettler et al., 2002; Ts'o et al., 1986), we assumed that contrast heterogeneity affects frequency detuning and physical proximity among annuli affects coupling strength among corresponding neural circuits. Hence, the starting point in this chapter is the realization that the mathematical factors that determine synchrony among weakly coupled oscillators can be linked to the stimulus features that guide figure-ground segregation.

If neural synchrony is indeed relevant for figure-ground segregation, one would expect that formalizing such a conceptual relation in a computational model would allow deriving quantitative predictions of figure-ground segregation performance from modelled synchronization behaviour. When the model was exposed to the texture stimuli, it revealed a triangular region of high synchronization in the space spanned by contrast heterogeneity (detuning) and grid coarseness (coupling strength). Remarkably, human participants who were asked to detect the figure from the ground in the same texture stimuli showed a quantitatively matched triangular region of supra-threshold figure-ground segregation performance for the same conditions. Interestingly, the model parameters chosen based on neurophysiological data in the macaque monkey were close to optimal to predict human figure-ground segregation performance. The consistency between model predictions and behavioural results suggests a mechanistic link between gamma synchronization in V1 and figure-ground segregation. This suggestion does not exclude that other mechanisms than the synchronization behaviour among neural groups in early visual cortex could contribute to figure-ground segregation. However, our data indicate at the very least that low-level neural synchrony is a viable mechanism for figure-ground segregation in the texture stimuli we used. Interestingly, participants' response times did not reveal an Arnold tongue as these were only affected significantly by contrast heterogeneity, but not by the physical distance between texture elements. This observation suggests that synchronization in V1 may not be a dominant factor in determining the speed of cortical information processing. Only after training-induced gains in synchrony and performance (see Chapter 4) did synchronization in our model become related to response times. This suggests a training-induced increase in the relevance of synchronization in the speed of cortical information processing. This finding will be discussed below. What can be inferred from the results of Chapter 3 is that the high stimulus dependency of gamma oscillations constitutes an essential aspect of the synchronization mechanism underlying figure-ground segregation. This dependency forms the basis of synchronization among figure elements (integration) and simultaneous de-synchronization between figure and ground elements (segregation). Therefore,

Chapter 3 shows that the high stimulus dependency of gamma oscillations may underlie, rather than preclude, a functional role in cortical information processing.

5-2-3. Chapter 4: Role of the Synchronization among Stimulus-dependent Gamma Oscillations in Perceptual Learning of Figure-ground Segregation

The fourth chapter addressed the question to what extent learning-induced changes in a phase oscillator model are predictive of human performance improvements in a figure-ground segregation task. In the third chapter, it was suggested that synchronization of gamma oscillations in V1 constitutes an important component of the neural mechanism that underlies figure-ground segregation. If this is indeed the case and if, as assumed in Chapter 2, synchronization behaviour is affected by experience-dependent changes in coupling strength, then any learning-induced gains in performance should be quantitatively related to learning-induced increases in neural synchrony. To evaluate this hypothesis, modelling was combined with psychophysics experimentation using the same stimulus conditions as in Chapter 3. Learning was incorporated into the model in the form of a three-factor learning rule that took phase coherence and the probability of correct responses on all trials of a session into account. Free parameters of the learning mechanism were estimated from the first two sessions, and subsequently used to predict learning effects in the remaining sessions. Results in Chapter 4 showed that synchrony and performance exhibit a close quantitative resemblance that was maintained across training sessions. In particular, the triangular region of supra-threshold accuracy data in a space defined by contrast heterogeneity and grid coarseness showed training-induced changes in shape that were closely matched by learning-induced changes in the Arnold tongue of the V1 oscillator model. Late in the training, an Arnold tongue emerged for response times as well. This further supports the idea that synchronization may be an important component of a neural figure-ground segregation mechanism and that learning-induced changes in figure-ground perception may at least in part be mediated by plasticity-induced changes in neural synchrony in a low-level visual area. The learning rule employed in Chapter 4 rested on the assumption that skill learning in early visual cortex is position specific (Merav Ahissar & Hochstein, 1996; Crist, Kapadia, Westheimer, & Gilbert, 1997; Karni & Sagi, 1991; A. A. Schoups, Vogels, & Orban, 1995). We verified this in a transfer session, in which figure-ground segregation was tested after moving the figure to the diametrically opposite visual field quadrant. Although figure-ground performance had increased significantly with training, it remained at baseline in the transfer

session. Overall, the psychophysical and modelling data in this chapter suggest that training-induced changes in synchrony in V1 may contribute to enhanced accuracy in figure-ground segregation in an expanded range of grid coarseness and contrast heterogeneity conditions. Moreover, towards the end of training, synchronization strength also becomes related to processing speed.

5-3. Theoretical Implications

The key conjecture of the present thesis is that oscillations are functionally relevant for neural information processing. In particular, the flexible synchronization behaviour of neural oscillators may underlie the flexible integration and segregation of stimulus-dependent and other types of information. This conjecture is central to two theories that feature prominently in neuroscience: the communication through coherence (CTC) theory (Fries, 2005) and the theory of weakly coupled oscillators (TWCO) (Ermentrout, Park, & Wilson, 2019; Pikovsky et al., 2003). CTC emphasizes long-range cortical interactions and proposes that synchronization within distributed neural networks facilitates selective communication (Fries, 2005). Specifically, it proposes that selective communication is achieved through coherence between oscillating activity in sending and receiving regions. However, CTC does not specify the mechanisms by which these regions synchronize in the first place. CTC simply states that two brain regions cannot communicate unless their activity patterns are in-phase (or more generally in a favourable phase-relation). Stated in this manner, CTC considers coherence as a prerequisite for communication. However, a crucial question is to understand how coherence is achieved in the first place, and therefore one may wonder if a form of communication needs to occur *prior* to the emergence of coherence. The latter idea is an essential aspect of the theoretical framework of TWCO, which stipulates that two brain regions may achieve synchrony through mutual interactions. In particular, TWCO formalizes and specifies the mutual interactions among oscillators under which specific phase relationships among two (or more) interacting oscillators can be achieved. As such, TWCO assumes that interaction precedes coherence. The opposition that is created here between CTC and TWCO may be overstated, and the two frameworks can be seen as compatible as long as one accepts that CTC is underspecified in terms of the mechanisms that enable the phase relations that in turn enable communication. Note that in joining the concepts of CTC and TWCO it is interesting to reflect on the meaning of the terms ‘interaction’ and ‘communication’. Interaction between two oscillators refers to the mutual influences that bring oscillators into a favourable phase-relationship that permits communication. If communication is defined as the

ability of action potentials from a sending population of neurons to trigger action potentials in a receiving population of neurons, then interaction may precede communication, because the interactions among connected oscillators will take place partly in time periods where communication as defined above is not (yet) possible. In this sense communication and interaction can be distinguished. However, at the same time, it is clear that the mutual interactions among neuronal pools occur through spiking, and that spikes from a sending population that arrive in an inhibitory period of a receiving population are still part of the interaction that leads to favourable phase relations required for action potentials from a sending population to trigger action potentials in a receiving population. From that perspective, the mechanisms of interaction and communication are closely related.

It is fascinating to note that TWCO is a general theory of synchronization phenomena, and that its concepts have been applied successfully and widely in chemistry, biology, and neuroscience (Ermentrout et al., 2019). As a general theory, TWCO is not concerned with whether or not oscillations and synchrony in the brain are relevant for neural information processing. However, a number of theoretical neuroscientists have over the years developed theories of neural information processing that are rooted in TWCO and that adhere to its fundamental principles. Noteworthy in this context is seminal work led by Izhikevich who suggested that synchrony allows for the flexible connection and disconnection of neural oscillators based on changing task demands (Hoppensteadt & Izhikevich, 1999; Izhikevich & Appl Math, 2006). At the macroscopic scale (involving long-range interactions), this concept is in line with dynamic routing of information to ensure that the output of local computations is sent to the appropriate brain regions for further processing. At the mesoscopic scale (i.e. within cortical areas), the flexibility of network synchronization may be utilized for local information integration and segregation such as required for associative memory (Hoppensteadt & Izhikevich, 1999) or figure-ground segregation. Depending on the spatio-temporal framework applied to the oscillator network and simulated data in Chapter 2, the findings in that chapter can be relevant in the context of a putative role of neural synchrony for long-range interactions². Specifically, Chapter 2 revealed that dynamic conduction velocity

² In the context of fast oscillations such as gamma, typical cortical conduction velocities (on the order of 100 meters per second (Swadlow & Waxman, 2012)) may manifest as significant delays for long-range connections (between cortical areas) but not for short-range connections (within cortical areas). The reason is that a) delays typically manifest as phase-shifts and b) the impact of phase-shifts is relative to oscillation periods. As a rule of thumb (and exactly for pure sine interaction function as employed in the Kuramoto model), only

provides the possibility for synchronization even in the context of fast synaptic changes promoting structural network segregation. This indicates that adaptive myelination may have the capacity to compensate for synaptic effects that might otherwise desynchronize neural groups. Adaptive myelination may thus help to stabilize dynamic routing in the context of synaptic changes in long-range connectivity. Chapters 3 and 4 speak towards a putative role of neural synchrony at the mesoscopic scale. Depending on stimulus properties, and on the excitatory drive delivered locally to the various neuronal populations encoding the stimulus, these neuronal populations may synchronize and hence form an integrated neural group that is segregated from other groups in a manner that is relevant for visual perception (Lowet et al., 2015). The stimulus dependence of synchronization renders this process highly flexible and hence perceptually relevant. Furthermore, synchronized neuronal groups within cortical regions, rather than entire cortical regions, likely form higher-order oscillators that interact at the macroscopic scale. This interplay between local information processing and global routing may constitute a highly flexible mechanism for cortical information processing (Kirst, Timme, & Battaglia, 2016).

Though not the focus of the present thesis, results in Chapter 4 are also relevant for an ongoing debate whether (location) specificity is a defining characteristic of perceptual learning. Several studies have reported that experience-induced improvements in perceptual skills are specific to the retinotopic location (Merav Ahissar & Hochstein, 1996; Crist et al., 1997; Karni & Sagi, 1991; A. A. Schoups et al., 1995) and stimulus features (Merav Ahissar & Hochstein, 1996; Merav Ahissar, Laiwand, Kozminsky, & Hochstein, 1998; M. Ahissar & Hochstein, 1993; Crist et al., 1997; Fiorentini & Berardi, 1980; Karni & Sagi, 1991; A. Schoups, Vogels, Qian, & Orban, 2001) of the trained skill. However, other studies have reported that skills can generalize to novel locations and stimulus features (Aberg, Tartaglia, & Herzog, 2009; Jeter, Doshier, Petrov, & Lu, 2009; R. Wang, Cong, & Yu, 2013; R. Wang, Zhang, Klein, Levi, & Yu, 2012; Zhang et al., 2010). The modelling work in Chapter 4 assumes that perceptual learning is location-specific. We validated this assumption empirically by including an additional session wherein it was shown that improvements on a figure-ground segregation skill do not generalize across retinotopic locations.

phase-shifts between $\frac{1}{2}\pi$ and $\frac{3}{2}\pi$ will notably affect synchronization behaviour (Ermentrout & Ko, 2009). For gamma oscillations, such phase-shifts may occur for long-range but not short-range connections.

5-4. Implications for the Role of Local Gamma

While TWCO is agnostic with regard to the role of specific frequency bands, gamma range oscillations were of particular interest in the present thesis. Chapters 3 and 4 suggest that gamma oscillations contribute to visual processing. These studies show that local and global image statistics drive an oscillatory mechanism for image segmentation. This is in line with a number of studies (N. Brunet et al., 2015; Gray & Goodell, 2011) that have reported the presence of gamma oscillations in macaque visual cortical areas, specifically in V1, during free viewing of static images. Specifically, Lowet et al. (2015), who in a modelling study using an online image database (Martin, Fowlkes, Tal, & Malik, 2001) showed a meaningful link between border segmentation in natural images by human observers and gamma synchronization among nearby neuronal groups driven by image contrast within their receptive fields. Lowet et al.'s study (Lowet et al., 2015) suggested that surface perception is related both to the smaller contrast variations (thus lower detuning) within surfaces in comparison to the large contrast variations (thus higher detuning) across surfaces, at the surface borders. This led to the integration (synchronization) of neural activity induced within each figure surface, and to the segregation of activity across surface borders. Lowet et al.'s study (Lowet et al., 2015) together with our own data (Chapters 3 and 4) provide support for the idea that gamma synchronization provides a means for grouping elements into wholes that reflect objects in a scene. The utility of a synchronization-based algorithm for (natural) image segmentation has also been demonstrated previously (Lowet et al., 2015; Yogendra, Chamika, Fan, Shim, & Roy, 2017).

While previous findings along with those presented in this thesis provide converging evidence for a role of local gamma in visual scene analysis, some studies have failed to detect gamma oscillations in response to moving (Kayser, Salazar, & König, 2003) and even static (Dora Hermes, Miller, Wandell, & Winawer, 2015; Ray & Maunsell, 2015) natural images. This absence of gamma oscillations in response to static natural images is surprising and suggests that gamma oscillations may be sufficient but not necessary for visual processing. This conclusion, however, may be premature. A failure to detect gamma oscillations does not imply their absence. Indeed, failure to detect gamma can be due to inadequate spatial resolution of electrophysiological recording methods. Images with low degree of structure (i.e., with a high degree of heterogeneity, randomness and many small elements) are reflected by unstructured patterns of gamma oscillations on the cortical surface with variations in frequencies and phases that are too closely spaced to be detected with

typical electrodes (N. M. Brunet & Fries, 2019). Electrophysiological recordings with insufficient spatial resolution may capture several neuronal pools whose gamma rhythms may cancel each other out. Furthermore, signals from asynchronous neural oscillations may mask signals from synchronous oscillations. Insufficient data and the effect of noise for detecting low gamma power in response to images with low degree of structure could be another factor preventing the detection of gamma oscillations. Interestingly, even if the absence of gamma *oscillations* in response to natural images turns out to be a credible observation, this does not preclude that neuronal synchrony may be necessary for visual processing. Hermes et al. (2015) reported the presence of non-oscillatory broad-band signals (around 80-200 Hz) during the processing of natural images. Given that even non-oscillatory signals can become synchronized (Thivierge, 2008), predictions based on the synchronization (of non-oscillatory signals) among neural groups may still hold true for figure-ground segregation in natural images.

The present thesis provides support for a functional role of gamma oscillations and their synchronization. The absence of gamma oscillations in some conditions is a weak argument to make broad claims about its irrelevance. Likewise, observations of variations in gamma frequency or transmission delays are a weak argument against the functional contributions of gamma oscillations in the absence of a theoretical framework specifying factors that regulate synchronization. A step forward in assessing a potential role of gamma in perception is through the development of biologically constrained theoretical/computational models that formalize a putative perceptual role of gamma and generate testable predictions. Our work follows this approach and provides quantitative support for a role of gamma oscillations and synchronization in figure-ground segregation.

5-5. Reflections on the Modeling Approach Presented in this Thesis

We will not reiterate the limitations in terms of modelling choices and/or experimental setup that are already discussed in Chapters 2-4. Instead, the general modelling approach followed in this thesis will be evaluated. Throughout the thesis, a neural mass model has been utilized that reduces the dynamics of neural communities to the interaction between simple phase oscillators. This may be regarded as too abstract for a model to yield plausible mechanistic accounts of neural and behavioural phenomena. This concern shall be addressed in the following sections in the light of a deeper examination of scientific models in general.

5-5-1. Ontology, Epistemology and Semantics of Scientific Models

Models are highly relevant in many scientific contexts. However, the exact role models play within science is highly dependent on the context and the type of model employed. Analogical models, phenomenological models, theoretical models, mathematical models, computational models, explanatory models, idealized models, scale models, animal models, and didactic models are but some of the different types of models that can be identified in the literature (Roman & Hartmann, 2020). The diversity of models renders it difficult to provide an overarching definition of what a model is, and of its purpose. Instead, it can be elucidating to consider models from the perspective of their ontology, their epistemology and their semantics.

The ontological perspective on models focuses on the question what kind of objects scientists are dealing with when they work with models. It is important to realize that a model does not need to be a theoretical or mathematical entity. The class of models contains a heterogeneous collection of different objects that belong to different ontological kinds. Some models are physical objects such as animal models used in the life sciences or wooden scale models used in aeronautical engineering. Other models are fictional or abstract models such as imaginary atoms, populations, or economies. Nevertheless, in the natural sciences, most models are indeed equations and other forms of stylized descriptions of a target system.

Epistemology poses the question what can be learned from models. Models serve several epistemological functions as they allow scientists to learn something about the models themselves as well as to learn something about their target systems; aspects of the world that are of scientific interest. Both the construction of a model and its manipulation afford opportunities to learn about the model (Morgan, 1999) and once scientists have knowledge about the model, they can transfer this knowledge to the target system through the derivation and validation of testable hypotheses.

Finally, semantics poses the question which target systems are represented by models, and in which manner. Before elaborating on this motion, it is useful to note that models do not always represent a target system and may be an object of study in their own right. In particular, when models are highly abstract and lend themselves to the investigation of many diverse phenomena, scientists may be interested in the model per se rather than any specific target system they may represent. However, more frequently, models are used as stand-ins for a specific target system, which allows scientists to form hypotheses about the target; i.e., to convert truths found in the model into claims about the target system. According to Hughes (Hughes, 1997),

this involves three steps. First, elements of the target system are *denoted* by elements of the model. The precise conditions that need to be met for a model to denote (or represent) a target are still a matter of debate among philosophers of science (Roman & Hartmann, 2020) and depend on the type and intended use of a model. *Phenomenological (descriptive) models*, for instance, only represent observable properties of their target systems and refrain from postulating underlying mechanisms (Bokulich, 2009). A Gabor function may, for instance, be used as a phenomenological model of the receptive field of a neuron in V1 in that it captures the neuron's activation profile in response to different stimuli. *Mechanistic (explanatory) models*, on the other hand, represent both the components and the causal relations between these components that together constitute the mechanism underlying a target system (Kaplan, 2011). A model of the receptive field of a neuron in V1 would thus need to specify the components (such as retinal receptors, thalamic neurons, connection profiles etc.) and their (causally relevant) interactions in order to be considered mechanistic. Second, models exhibit internal properties and dynamics that allow researchers to *demonstrate* theoretical conclusions. This step takes place entirely within models and is thus removed from the target system. Finally, the results of these demonstrations are *interpreted* in terms of the target. The last step is necessary because demonstrations establish results only about the model itself, and only in interpreting these results can the model user draw inferences about the target, which can be used as hypotheses for experimental research.

5-5-2. Mechanisms and Idealizations

The central endeavour of science is to explain and understand natural phenomena. Though explanation and understanding are closely related, they are nevertheless distinct cognitive functions and this translates directly into how they affect scientific modelling. Models are considered to be explanatory of a target phenomenon if they meet the mechanism-model mapping (3M) criterion; i.e., if there is a mapping between elements in the model and elements in the mechanism that produces the target phenomenon (Kaplan, 2011). Explanatory models are thus mechanistic models. This implies that a) the variables in an explanatory model correspond to identifiable components and organizational features of the mechanism that produces, maintains or underlies the phenomenon and b) dependencies posited among variables in the model correspond to causal relations among the components of the target mechanism. Inclusion of model elements that take additional mechanism components into account as well as faithful representations of causal relations among mechanism components are generally considered to yield better

explanations of the target phenomenon (Boone & Piccinini, 2016; Kaplan, 2011). However, this does not necessarily improve understanding. In fact, due to humans' limited cognitive capacity, understanding may be hampered by excessive mechanistic fidelity and detail (Elgin, 2017). Indeed, understanding benefits from idealizations, such as deliberate distortions and omissions, and from abstractions (Humphreys, 1995; Strevens, 2004, 2008; Weisberg, 2007b).

Philosophers of science generally distinguish two major types of idealization, distortive idealization and minimalist idealization. Distortive idealizations involve simplifications that introduce deliberate distortions of the target such as point masses moving on frictionless planes or perfectly rational economic agents (Roman & Hartmann, 2020). Interestingly, distortive idealization is often not justified in terms of facilitating understanding and accommodating the limited capacity of our mental apparatus. Instead, distortive idealization may be justifiable in terms of computational tractability; i.e., the ability to analyze/simulate these models on existing hardware. Therefore, it is often argued that with advances in computational power and mathematical techniques, models should be de-idealized (McMullin, 1985). It is a matter of debate, however, whether this is possible without dismantling the models altogether (Batterman, 2002, 2010; Rice, 2015, 2019).

Minimalist idealization involves limiting models only to core causal factors; i.e., only those factors that make a difference in the occurrence of a target phenomenon (Strevens, 2003). In contrast to distortive idealization, minimalist idealization involves no commitment to de-idealization. The focus of the minimalist idealization approach on core causal factors roots its justification deeply in considerations of our restricted understanding due to limited cognitive capacity. Note that idealized models may still be considered mechanistic as long as they abide by the 3M criterion to the extent that there is a mapping between *at least one* element in the model and *at least one* element of the mechanism that produces the target phenomenon (Kaplan, 2011). Indeed, a common view is that abstracting away from irrelevant details may be as important to mechanistic explanation as including relevant details (Boone & Piccinini, 2016; Piccinini & Craver, 2011). Idealization thus serves an important role in science and the resulting models can arguably still be considered mechanistic. This does not mean that the practice of developing models that exhibit a high degree of mechanistic fidelity and detail is not important. Indeed, it is probably best practice to construct multiple models for any particular target phenomenon that exhibit varying degrees of mechanistic fidelity and detail. This allows scientists to seek an appropriate trade-off between explanation and understanding (Levins, 1966; Odenbaugh, 2003; Weisberg, 2007a, 2015).

5-5-3. Models in Computational Neuroscience

What holds true for scientific models in general, also applies to models in computational neuroscience. However, models in neuroscience, and biology in general, differ from models in disciplines such as physics and chemistry. In contrast to physics and chemistry, biology often deals with target systems that perform functions (Piccinini & Shagrir, 2014). In case of the brain, this function is arguably to perform information processing that allows animals (including humans) to interact with a dynamic environment in a meaningful way (i.e., such that the animal may survive and reproduce). This abstract function is typically decomposed into subordinate functions such as visual object recognition or the coordination of grasping movements that are performed by individual neural structures and processes that serve as targets for computational neuroscientists. This implies that the target systems studied by neuroscientists exhibit both, what may be termed, *(bio)physical* and *functional* phenomena and both need to be explained and understood. This requires computational neuroscientists to take a somewhat different perspective in constructing their models than, for example, a theoretical physicist. In addition to specify the physical, chemical and biological elements of neural structures and their causal interactions, computational neuroscientists also need to think about their computational and representational properties and functional purpose (Marr, 1982). When considering the neuronal membrane, for instance, computational neuroscientists need to specify physical and chemical properties such as voltage, conductance, capacitance, the presence of voltage- and/or chemically-gated ion channels, their dynamics and interactions in order to provide a mechanistic model of action potentials. In this aspect, the work of a computational neuroscientist is similar to (and may draw from) that of a theoretical physicist. However, computational neuroscientists also need to understand how information about external stimuli or intrinsic states is encoded and transmitted by action potentials and how this is functionally relevant. By contrast, a theoretical physicist who is interested, for example, in vortex shedding in fluids does not need to be concerned with any notions of representation or computations performed by the fluid. Within neuroscience, only the combination of the *(bio)physical* and *functional* perspective provides a complete account of neural target systems. An interesting advantage is that this enables scientists to draw testable *functional* conclusions from *biophysical* models and vice versa, thus raising the informative content of their models and hence their testability and falsifiability (Popper, 2014).

5-5-4. Models in the Present Thesis

It is now possible to evaluate the models used in the present thesis as well as the modelling approaches that were employed. All models in the present thesis utilized the Kuramoto equation, an abstract coupled oscillator model that can be used to study many kinds of synchronization phenomena (see Acebr et al., (2005) for a review). The ontology of the model is thus shared between chapters. However, Chapter 2 differs from Chapters 3 and 4 in terms of semantics and epistemology. Specifically, in the second chapter, the model should be considered to be inspired by properties of neural systems in general rather than to represent any specific neural target system. Hence, in Chapter 2, the model was the object of study in its own right. In this case, the question whether the model is appropriate, in the sense of whether the model can adequately represent a particular target system, is no longer pressing. What is relevant is whether the model can, in principle, represent some target systems. In the specific case of Chapter 2, we investigated the effects of adaptive coupling strength and of adaptive transmission delays on the collective behaviour of weakly coupled oscillators. This can be relevant to any synchronization phenomenon wherein coupling strength and transmission delays are adaptive. This is the case for neural oscillations and synchrony (Pajevic et al., 2014). The results in the second chapter were interpreted within this context. However, the conclusions that can be drawn from the second chapter are conclusions about the model and not conclusions about the brain. They only hint at new possibilities (such as a dissociation between structure and function) and future avenues for brain research, and any parallels we have drawn with specific brain processes in that chapter are to be considered with caution.

In contrast to the model in Chapter 2, the model presented in Chapter 3 and expanded in Chapter 4 does represent a specific target system; namely a network of oscillating neuronal populations in early visual cortex. However, individual neuronal populations were not modelled as circuits of excitatory and inhibitory neurons but instead by simple phase oscillators. Likewise, coupling between populations was not modelled in the form of synaptic interactions between neurons but instead by a simple (sinusoidal) coupling function. This raises the question in what sense the model represents neural processes in a sufficiently mechanistic manner. To answer this question, it is important to keep in mind the purpose of the model. The model was intended to represent *networks* of oscillating neuronal populations in early visual cortex. Therefore, it is possible to abstract away from the detailed neuronal and synaptic processes that give rise to interactions among individual populations that underlie the oscillations (Bartos, Vida, & Jonas, 2007; Hansel & Mato, 2003; X. J.

Wang & Buzsáki, 1996; Miles A. Whittington, Traub, & Jefferys, 1995; Wilson & Cowan, 1972), and focus instead on interactions among the oscillations at the population level. Whether the Kuramoto model is an appropriate choice for such an abstraction depends on whether it captures the synchronization behaviour of synaptically coupled neuronal circuits. Prior research has shown that this is indeed the case. It has, for instance, been shown that networks of quadratic integrate-and-fire, Izhikevich and Hodgkin-Huxley neurons as well as Winfree-type ensembles of oscillators exhibited synchronization behaviour comparable to that in networks of Kuramoto oscillators (Bhowmik & Shanahan, 2012; Lowet et al., 2015; Politi & Rosenblum, 2015). The chosen model can thus generally represent neural oscillator networks. To specifically represent neural oscillator networks in V1, elements of the model need to denote elements of this particular target system. These elements are the retinotopic organization of neuronal populations in V1, the distance-dependence of horizontal coupling and the relation between the contrast in an oscillator's population receptive field and their intrinsic frequencies in the gamma range. In Chapter 4, a learning algorithm was added to the model. The denotationally relevant elements of this are the eligibility of individual weights to change based on the co-occurrence of pre- and post-synaptic activity, and reward in response to synchronization behaviour. All of these are based on extensive pre-existing literature (Chubykin, Roach, Bear, & Shuler, 2013; Diekelmann & Born, 2010; Gerstner, Lehmann, Liakoni, Corneil, & Brea, 2018; He et al., 2015; Izhikevich, Jay, Drive, & Diego, 2007; Rasch & Born, 2013) as well as electrophysiological data (Lowet et al., 2017) in order to maximize their biological fidelity. The model thus specifies relevant components in early visual cortex and their interactions that are considered to be part of the mechanism that gives rise to neural synchrony in the gamma range. It further provides a mapping between elements in the model and elements in this mechanism. As such, the model may be considered mechanistic according to the 3M criterion. However, only the core causal factors were included in this specification, rendering the model a minimalist idealization.

Chapters 3 and 4 then proceeded to demonstrate how synchronization behaviour in the model depends on stimulus conditions and training-induced changes in coupling. This was interpreted to reflect synchronization behaviour among neuronal populations in the corresponding patch of V1. Importantly, from an epistemological perspective, the work conducted in these chapters was not intended to provide novel insights regarding the synchronization behaviour of neuronal populations in V1. This would have been the case, if the work was primarily intended to study *biophysical* phenomena, which could have been investigated, for example, with *in vivo* and *in vitro* recording methods (Jehee, Ling, Swisher, van Bergen, & Tong, 2012; Lowet et

al., 2017; A. Schoups et al., 2001; Shibata, Watanabe, Sasaki, & Kawato, 2011; Z. Wang et al., 2021; Yan et al., 2014), perhaps combined with optogenetic manipulations (Kirchberger et al., 2021). Instead, we intended to study *functional* phenomena and, specifically, to test the hypothesis that synchronization behaviour in our minimalist idealization of the target system could be predictive for perception. In order to do so, it is important to consider both the modelling and experimentation conducted within these two chapters and to view this approach from a falsification perspective. In essence, the work in Chapters 3 and 4 rests on two premises. First, *synchronization in the employed oscillator model reflects synchronization in V1*. Second, *synchronization in V1 has observable (i.e., testable) perceptual consequences*. This premise is the core hypothesis of Chapters 3 and 4. These premises together warrant the conclusion that *synchronization in the employed oscillator model has observable (i.e., testable) perceptual consequences* and rejection of the conclusion (i.e., failure to empirically verify model predictions) means that either the first, second or both premises are false. The first premise is supported not only by the care taken to ensure the model is an appropriate representation of the relevant components and processes in V1 but also by independent neurophysiological data (Lowet et al., 2017). Rejection of the conclusion must then entail rejection specifically of the second premise and hence falsification of the core hypothesis of the two chapters. Experiments in both chapters failed to falsify this hypothesis, thus rendering it tentatively acceptable. Therefore, we suggest that it is reasonable to conclude that synchronization mechanisms in V1 contribute to human perceptual performance.

The preceding overview of the scientific practice of modelling as well as analysis of the work presented in the core chapters of this thesis warrant the conclusion that, given the respective objectives of the three chapters and their accompanying requirements regarding modelling approaches, the employed models can indeed be considered adequate for their intended purposes.

5-6. Future Directions

The work presented in the present thesis may provide the impetus for several further research lines. First, the present focus on *function* may be supplemented by work focusing on *biophysics* in order to arrive at a more holistic understanding of gamma oscillations and synchrony in early visual cortex. This would involve both empirical and modelling work. The former might entail a replication of the studies presented in Chapters 3 and 4 using electrophysiological recordings in monkeys. The latter might entail translating the current model to a spiking neuron implementation

wherein local (columnar) oscillations are driven by external inputs in conjunction with recurrent interactions among intracolumnar excitatory and inhibitory neuronal populations, wherein synchrony may be the result of lateral interactions between columns. A combination of monkey electrophysiological and behavioural results with detailed biophysical modelling would permit a thorough validation of the proposed synchrony-based information integration mechanism at the biological and behavioural level. Introducing a biologically realistic laminar profile to the columnar model would additionally allow for studying the spatio-temporal profiles of feedforward, lateral and feedback (e.g., attention) signals and how they interact during visual scene analysis (Brosch, Tschechne, & Neumann, 2016).

The interaction between feedforward, lateral and feedback signals is also relevant from an extended functional perspective. While the present thesis provides evidence that local gamma may be relevant for figure-ground segregation, it is likely that it is merely one component of a larger mechanism that involves several cortical and subcortical structures. Another avenue for further research would therefore be the development of a large-scale model that leverages oscillations and synchrony to perform scene analysis in natural stimuli. Such a model should be able to segregate image regions corresponding to different objects and integrate those regions corresponding to the same object. This is a challenging task that requires a hierarchical neural architecture exhibiting feedforward, lateral and feedback connections. Notably, such a model should strive to unify the local synchronization mechanisms detailed in the present thesis with border reconstruction and filling-in mechanisms proposed by other groups (Poort, Self, van Vugt, Malkki, & Roelfsema, 2016; Roelfsema, Lamme, Spekreijse, & Bosch, 2002; Self, Kooijmans, Supèr, Lamme, & Roelfsema, 2012). An important validation for such a model, besides realistic perceptual performance, would be its ability to account for neurophysiological observations demonstrating the necessary contributions of feedback for figure-ground segregation, following an initial feedforward sweep (Kirchberger et al., 2019; Lamme, Supèr, & Spekreijse, 1998; Supèr & Lamme, 2007).