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# Pacemaker and Network Mechanisms of Neural Rhythm Generation

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## 1. Introduction

The origin of flexible rhythmic activity in brain circuits, or even in smaller neural networks, like central pattern generator (CPG) motor networks, is still not fully understood. The main unresolved questions are (i) what are the respective roles of intrinsic neuronal rhythms and network based dynamics in systems of coupled, heterogeneous, intrinsically complex, even chaotic, neurons? and (ii) what mechanisms are underlying the coexistence of robustness and flexibility in the observed rhythmic spatio-temporal patterns?

One common view is that particular neurons provide the rhythmogenic component while the connections between different neurons are responsible for the regularization and synchronization of groups of neurons and for specific phase relationships in multi-phasic bursting patterns. The opposing view is that constituent neurons are by themselves non-rhythmogenic and the emergence of rhythmic bursting behaviors is entirely due to the network interactions. The reality is more interesting and challenging, especially, when we are concerned about the brain. Usually, different mechanisms of rhythm generation coexist in the brain and rhythms from different sources and different levels of integration interact closely. It is important to emphasize that fast rhythms and slow rhythms need different levels of abstraction for describing and understanding them. It is reasonable to consider three such levels: (i) the neuronal level, (ii) the neuronal module or neuronal mass level, and (iii) the mental mode level. The analysis of low frequency ( $< 0.1$  Hz) oscillations, for example, needs coarse-grained models of the interaction of mental modes, i.e., perceptual, cognitive and emotional modes.

The chapter is organized in the following way. In the first part (neuronal level) we describe the results of computer simulations examining how spatio-temporal rhythmic patterns emerge in motif networks of Hodgkin-Huxley (H-H) neurons connected by slow inhibitory synapses with a non-symmetric pattern of coupling strengths. We demonstrate that the interplay between intrinsic and network dynamics can lead to either cooperation or competition, depending on three basic control parameters identified in the models: (i) the shape of intrinsic bursts, (ii) the strength of the coupling between neurons and (iii) the degree of asymmetry in the connectivity matrix.

The cooperation of intrinsic dynamics and network mechanisms is shown to correlate with bistability, i.e., the coexistence of two different attractors in the phase space of the system

corresponding to different rhythmic spatio-temporal patterns. In contrast, if the network mechanism of rhythmogenesis dominates, monostability is observed with a typical pattern of winnerless competition between neurons. The analysis of bifurcations between the two regimes reveals how they provide robustness and flexibility to the network performance.

In the second part of the chapter (neuronal module level) we discuss the interaction of different motif networks that produce rhythmic activities and analyze their (periodic or chaotic) cooperative dynamics. One of the promising applications of the general analysis is building a mathematical theory for hippocampal theta rhythms known to be crucial for spatial memory. It is interesting that the interaction of two or more core motif networks could generate chaotic rhythms with very specific dynamical features that we discuss in detail here. We also analyze here the interaction of network oscillations with external periodic fields. One aspect that we have investigated in detail is heteroclinic synchronization that can explain the coordination of different rhythms in the brain (see Fig 6).

In the third part of the chapter (mental mode level) we describe rhythmic mental dynamics. In particular, based on an ecological model of cognitive and emotional modes that compete for energy and informational resources, we have discovered a new instability that can be the origin of low frequency oscillations in the brain. It is an envelope or modulation instability that is typical for the brain resting state. Our modeling has demonstrated the emergence of pulsations of brain activity with a time scale of about 25-30 s. The mathematical object that represents this rhythmic activity is a heteroclinic cycle that appears in the phase space of the three clusters of modes which we identify as the cognitive, emotional and resources clusters.

## 2. Small neuronal motif networks

Oscillatory neural circuits and, in particular, central pattern generators (GPGs) contain both basic rhythmogenic and pattern forming mechanisms. A question fundamental to such networks is how the specific intrinsic activity of individual neurons can be constrained by synaptic dynamics and network organization and, conversely, how the network output emerges from the cooperative activity of the network components.

Over the last three decades, neurophysiologists have proposed two different mechanisms for the generation of neuronal network oscillations: rhythmogenesis by one or more pacemaker neurons and rhythm generation by network mechanisms. Pacemaker mechanisms are based on a single neuron, or a synchronized neural group, that generates bursting activity as a result of intrinsic cellular properties, while the rest of the network orchestrates the phase relationships between different principal cells (or cell groups) to generate a specific spatio-temporal pattern (Rabinovich, Huerta, Varona & Afraimovich, 2006; Selverston & Miller, 1980; Yuste et al., 2005; Buzsaki, 2006; Kopell et al., 2005; Börgers et al., 2005). In network-based rhythm generation the spatio-temporal dynamics result from the excitatory and inhibitory synaptic connections between neurons, which do not have intrinsic rhythmic activity. In this case, networks of tonically spiking neurons are able to generate rhythmic bursts as a result of a cooperative, synapse-mediated, modulational instability (Nowotny & Rabinovich, 2007).

Rhythmogenesis based on inhibition has been studied extensively in the past (see e.g., (Whittington et al., 2000) for a review). However, the existing theoretical work was often focused on networks with symmetric reciprocal inhibition. In this earlier work it has been well established that, depending on synaptic characteristics (e.g synaptic timescale, synaptic depression) and intrinsic neuronal characteristics (e.g. spike frequency adaptation) the

inhibition between two neurons can produce synchronous or anti-phase activity (Calabrese, 1995; Wang & Rinzel, 1993; Skinner et al., 1994). Concurrent gap-junction coupling is, furthermore, known to complement burst generation through inhibition and its synchronization (in-phase or anti-phase) (Skinner et al., 1999; Mancilla et al., 2007). These ideas have shown a vast potential for modeling coordination, memory and decision-making tasks like artificial CPG design (Lewis et al., 2003) or the two-interval discrimination problem (Machens et al., 2005). Generalization to two competing neural populations in the context of explaining binocular rivalry yields essentially similar phenomena (Tong et al., 2006). The emphasis was typically on the case of symmetrical coupling, because asymmetry seemed to add little qualitative change to the dynamics, if any.

Another approach is analyzing symmetry breaking bifurcations and arising stable heteroclinic cycles (the image of alternating neural activity) in networks with ring topology (Buono et al., 2000; Golomb & Ermentrout, 2002). In this case the symmetry of coupling strengths was the key demand for the analytical treatment to be fulfilled. A step towards understanding the principal role of asymmetry in the rhythmogenesis in multi-cell motifs was made in a series of papers by (Rabinovich et al., 2001; Afraimovich et al., 2004; Rabinovich et al., 2008) and (Nowotny & Rabinovich, 2007). They revealed the origin of sequential bursting activity in inhibitory spiking neural ensembles (the minimal motif had three neurons). These oscillations were shown to bifurcate from stable heteroclinic sequences in the phase space of the network. Moreover, it was proved that sequences are uniquely determined by the given asymmetry of the network.

Little is known about the dynamical principles that govern the interplay between intrinsic bursting and network mechanisms when both are found in a single system. There is growing experimental evidence suggesting that in some neural systems, like the respiratory CPG of mammals, the rhythm is generated by a combined pacemaker-network mechanism (Johnson et al., 2007; Rybak et al., 2004; 2007; Calabrese, 1998; Sohal et al., 2006), in this case operating on a distributed population of coupled, bursting pacemaker neurons. It has been suggested that such hybrid mechanisms of rhythmogenesis are potentially more robust, more reliable and more flexible than mechanisms based on pacemakers or network topology alone. They may, therefore, be more frequently at work in neuronal systems than previously assumed, which motivated us to examine their fundamental dynamical properties.

## **2.1 From tonic-spiking neuronal activity to network bursting**

There is a growing body of evidence that slow brain rhythms are generated by simple inhibitory neuronal networks. Sequential switching emerging from a modulation instability of tonic spiking activity is a widespread phenomenon underlying such rhythms. A basic dynamical system demonstrating reproducible switching is a network or motif realizing the Winnerless Competition Principle (WLC) (Rabinovich et al., 2001; Afraimovich et al., 2004). Below we analyze a minimal, reciprocally connected motif of three spiking units and explore observable dynamical regimes and transitions between them. We show that a tonic spiking regime loses its stability due to a Neimark-Sacker bifurcation. As computer modeling suggests, a heteroclinic cycle appears at the moment of bifurcation.

In general, the dynamical image of the bursting dynamics for the network-induced bursting is an attractor (limit cycle or strange attractor) in the vicinity of the heteroclinic manifold, which consists of saddle limit cycles and one-dimensional separatrix manifolds connecting them (see Fig. 1). The saddle limit cycles correspond to spiking in one of the neurons while

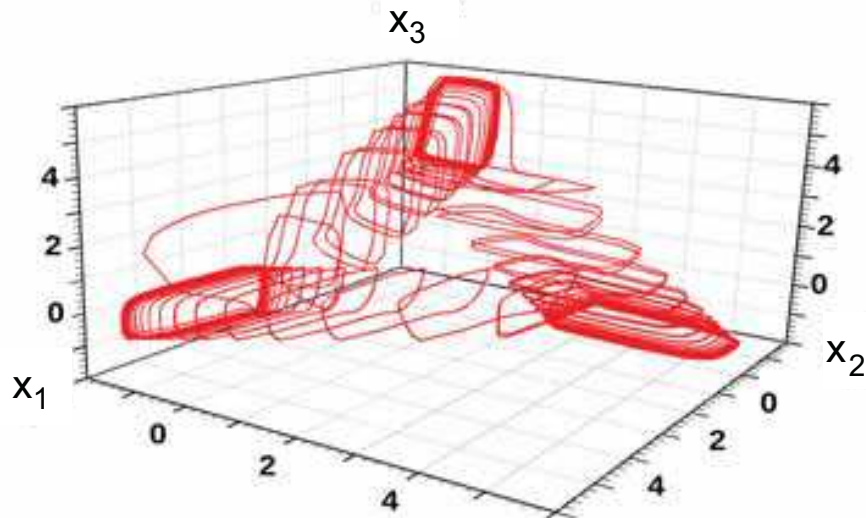


Fig. 1. Heteroclinic cycle (image of rhythmic bursting activity) in a 3D projection of the motif's phase space. Modified from (Rabinovich et al., 2000)

the others are silent. The sequential visits of the system to the neighborhoods of the saddle cycles is the origin of a periodic switching dynamics between silence and spiking in all neurons. The strength of the asymmetric inhibition between neurons determines the proximity of the attractor to the saddle cycles and the frequency of the network dynamics (Rabinovich, Huerta & Varona, 2006). The stronger the inhibition, the closer the attractor is to these saddles. To begin with, let us analyze the motif dynamics with a small network of simple spiking neurons described by the Bonhoeffer-Van der Pol model

$$\tau_1 \frac{dx_i(t)}{dt} = x_i(t) - \frac{1}{3}x_i^3(t) - y_i(t) - z_i(t)(x_i(t) - V) + S_i, \quad (1)$$

$$\frac{dy_i(t)}{dt} = x_i(t) - by_i(t) + a, \quad i = 1, \dots, 3, \quad (2)$$

which are connected by an inhibitory synaptic coupling described by

$$\tau_2 \frac{dz_i(t)}{dt} = \sum_j g_{ij}F(x_j) - z_i(t), \quad (3)$$

where  $x_i(t)$  denotes the membrane potential of the  $i$ th neuron,  $y_i(t)$  the variable corresponding to the action of all ionic currents,  $S_i$  the external stimuli to each neuron,  $V$  the reversal potential,  $g_{ij}$  the coupling coefficients between the  $i$ th and  $j$ th neuron and  $F(x_j) = 1/(1+\exp((0.5-x_j)/20))$ . The values of the parameters are fixed in all simulations to  $a=0.7$ ,  $b = 0.8$ ,  $\tau_1 = 0.08$ ,  $\tau_2 = 3.1$ , and  $V = -1.5$ , and we chose the parameter  $S_i > 0.35$  which corresponds to the tonic spiking regime of individual uncoupled neurons. Depending on the level of asymmetry of the inhibitory coupling, this simple network demonstrates a variety of dynamical regimes. In particular, regimes in which (i) one of the neurons generates tonic spiking and two other neurons are suppressed, (ii) two neurons are active and one is suppressed, (iii) all three neurons exhibit synchronous in-phase spiking oscillations ( $x_1 = x_2 =$



$x_3$ ), and (iv) sequential bursting activity emerges. In terms of the dynamical system, a stable limit cycle (of tonic spiking) transforms after bifurcation into a saddle cycle. Local bifurcation analysis and computer modeling of the global network dynamics of the system described by (1)-(3) was performed in (Komarov et al., 2009). The local bifurcation that corresponds to a modulation instability was identified to be a Neimark-Sacker bifurcation. In a dynamical system with discrete time (an iterated map) this bifurcation is characterized by the birth of a closed invariant curve from a fixed point when the fixed point changes stability via a pair of complex eigenvalues with unit modulus. We are interested in a subcritical Neimark-Sacker bifurcation, which results in an unstable limit cycle (within an invariant two-dimensional manifold). When this happens in the Poincaré map of a limit cycle, the bifurcation generates an invariant two-dimensional torus in the corresponding dynamical continuous time model (Kuznetsov, 1998). The stable two-dimensional torus is a geometrical image of stable rhythmic burst oscillations.

To analyze the emergence of such a regime it is necessary to investigate the dependence of the Floquet multipliers of the limit cycles which correspond to tonic spiking regimes on the control parameters  $\alpha_i = g_{ij}/g_{ji}$ , i.e., the degree of asymmetry of the inhibitory coupling strengths. In the absence of resonance the modulation appears when two conjugate complex multipliers reach the unit circle. Fig. 2 illustrates how multipliers change with increasing asymmetry of inhibitory connections. For the parameters of the system (1)-(3) a heteroclinic torus appears when the asymmetry of the connections becomes strong enough, i.e.,  $\alpha_i \gg 7.36 > 1$ .

When considering biologically more plausible Hodgkin-Huxley neurons, the analysis of the global bifurcations of the phase portrait of the motif dynamics becomes quickly analytically and numerically intractable. Nowotny & Rabinovich (2007) demonstrated, however, that if no resonance between cooperative bursting and individual neuronal spiking dynamics exists, an elegant direct reduction of the H-H model to an average (rate) description of the activity of individual neurons can be used to analyze the bifurcations of the system. The results of this analysis, comparing the bifurcations of the model at the two different levels of description, are presented in Fig. 3.

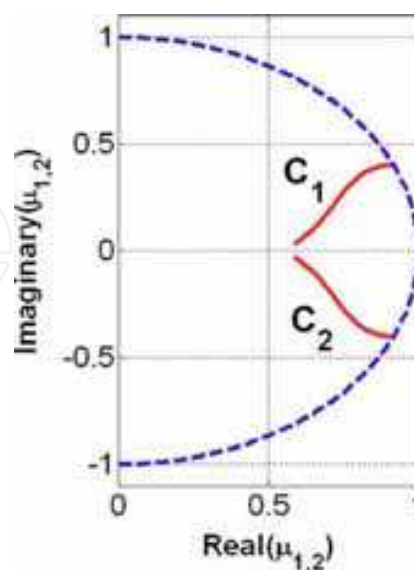


Fig. 2. The trajectories of two complex conjugate Floquet multipliers (red lines) as the system (1)-(3) approaches a Neimark-Sacker bifurcation. The bifurcation occurs when the multipliers reach the unit circle (dashed blue line). Modified from Komarov et al. (2009)

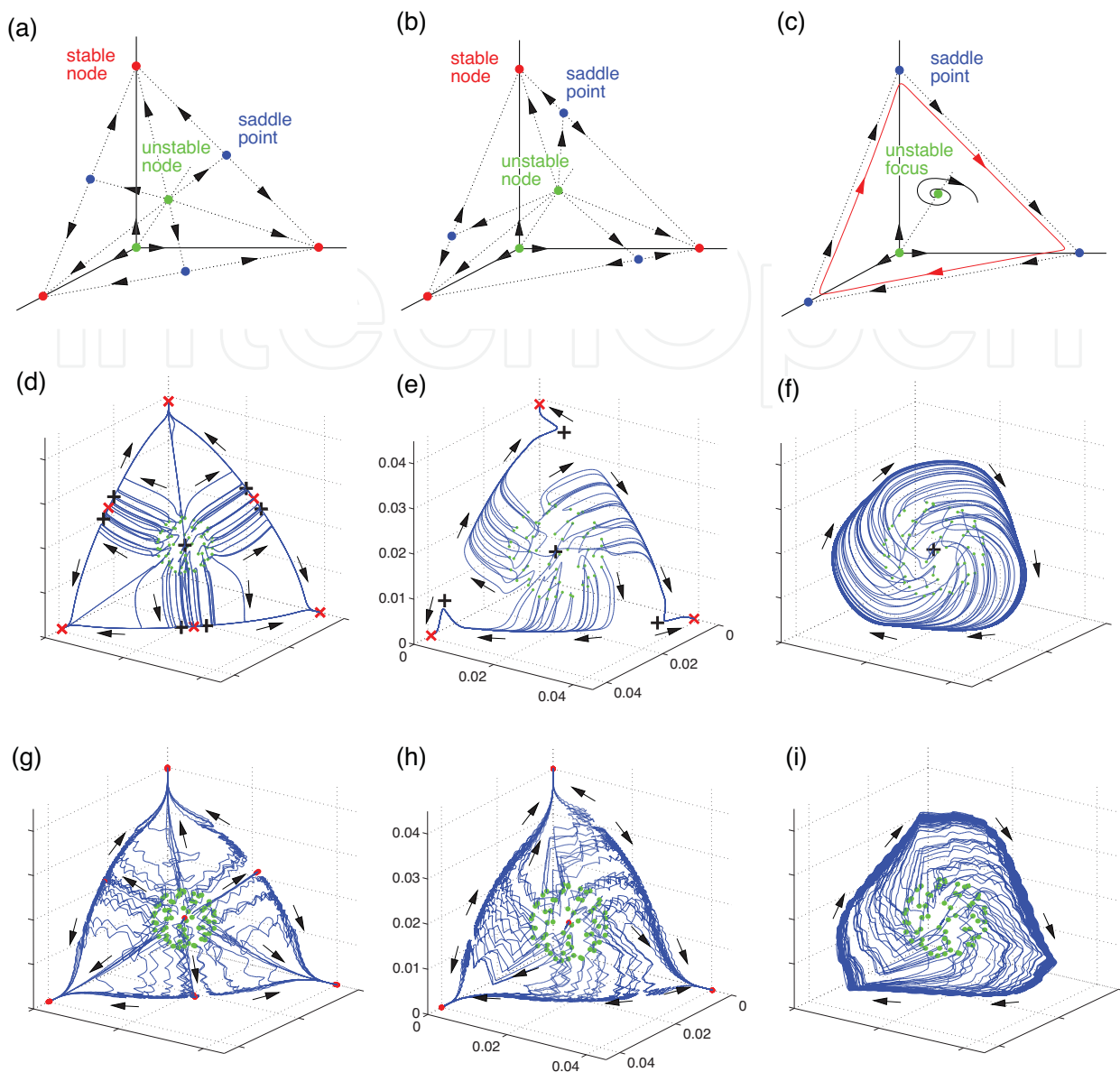


Fig. 3. Bifurcation towards rhythmic bursting in the Lotka-Volterra model, a biologically more plausible H-H type circuit model, and its average rate description. The Lotka-Volterra model with three units (a-c), undergoes a simultaneous saddle-node bifurcation in the three corners of the shown phase space simplex with increasing asymmetry of the connections (red points – stable fixed points (FP), blue points – saddles, green points – unstable FP). Numerical evidence for a similar bifurcation can be found in a system of realistic Hodgkin-Huxley neurons (g-i) (Nowotny & Rabinovich, 2007). This is confirmed by a systematic reduction of the biophysical Hodgkin-Huxley model to an equivalent rate model (d-f) and a subsequent numerical bifurcation analysis (red and black crosses in d-f denote the calculated FPs – red crosses are stable FP and black markers are FP with at least one unstable direction (saddles or unstable FP)). Modified from (Nowotny & Rabinovich, 2007)

The modulation instability that is related to a sub-critical Neimark-Sacker bifurcation is a general mechanism of the emergence of Low Frequency Oscillation (LFO) on all levels of neural network complexity (see also below). The necessary condition for such an instability

is a non-symmetric competition between agents, i.e., neurons, oscillating neuronal masses, or mental modes.

## 2.2 Competition-cooperation of bursting neurons in inhibitory networks

Let us now analyze bifurcations between the pacemaker and network regimes and understand how they provide robustness and flexibility to the network performance. Based on a simple model network (a motif, see e.g., (Sporns & Kötter, 2004; Milo et al., 2002; Zhigulin, 2004)) of three conditionally bursting Hodgkin-Huxley (H-H) type neurons with reciprocal inhibitory coupling, we elucidate some of the important properties of pacemaker-network interactions (Ivanchenko et al., 2008). The model network was inspired by the stomatogastric system of lobsters and we use the term conditional to signify that the biological bursting requires the presence of appropriate neuromodulators. In the model this corresponds to the presence of appropriate de- or hyperpolarization of the somatic compartment. The model neurons are similar to the lateral pyloric (LP) neurons in the lobster *Panulirus interruptus*, which normally burst irregularly when isolated. The model neurons also mimic real LP neurons in that being depolarized causes them to burst at higher frequencies and with longer bursts and being hyperpolarized slows the burst frequency down and decreases the burst duration (Nowotny et al., 2008). Furthermore, similar to the graded synapses in the lobster stomatogastric CPG, the model synapses are slow enough to implement an interaction between bursts rather than responding to single spikes. We are interested in the drastic changes (bifurcations) in the network dynamics which occur when the strength of intrinsic pacemaker activity is altered by passage of DC current and/or when the strength of the synaptic connections changes. The two-compartment neuron model used in this study was built based on voltage clamp recordings and extensive fits to data from isolated lobster LP neurons (Nowotny et al., 2008). The LP neuron plays an important role in the dynamics of the pyloric CPG of the lobster and is known to be a conditional burster with a wide range of dynamics from tonic spiking to irregular spiking, chaotic bursting, and regular bursting for polarizations ranging from depolarization to increasing levels of hyperpolarization. The LP neuron model is particularly well suited for our purposes because it replicates this wide range of dynamics. As we have already mentioned, burst generation in the circuit is based on two separate mechanisms.

**Intrinsic bursting:** In this case the synaptic connections determine the relative phases and detailed timings of the bursting activity of the pacemaker-type neurons. Pacemaker neurons can drive single-phase rhythms, such as heartbeat, by themselves and in synaptically connected clusters they can produce multi-phase rhythms as seen in the pyloric CPG in lobster. It has generally been assumed that pacemaker neurons lend a degree of robustness to rhythmic systems and they have indeed been found in almost all small circuits that have been described.

**Network bursting:** Here, the mechanism of rhythmogenesis is a modulation instability of the network (also known as winnerless competition). The constituent neurons of the circuit are tonic spiking neurons and the sequential bursting emerges due to synaptic interactions for sufficiently asymmetric connections between the neurons of the motif (Rabinovich et al., 2001; Afraimovich et al., 2004; Rabinovich et al., 2008). The sequence of bursting is uniquely determined by the network structure: in our case the chosen asymmetry of the inhibitory synapses will usually select a clockwise sequence of bursts; a reversal of the asymmetry would produce an opposite temporal sequence by default. This mechanism does not depend on the details of the dynamics of the constituent neurons other than that they are



intrinsically active (Nowotny & Rabinovich, 2007). An example of a network bursting system of Hodgkin-Huxley neuron is illustrated in figure 4. In this particular example, the system undergoes a bifurcation with increasing intrinsic excitability of the neurons, in which the heteroclinic orbit underlying network bursting becomes stable and causes an infinite slowdown of the bursting dynamics (Fig. 4c and d).

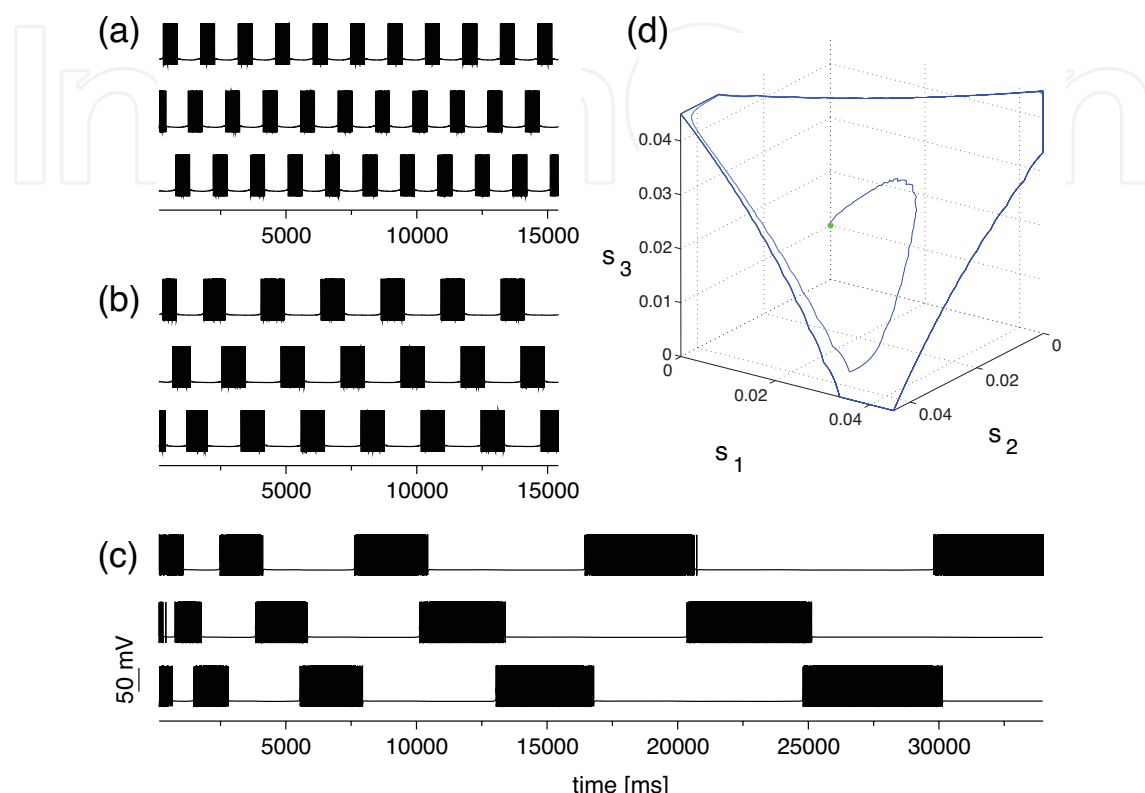


Fig. 4. Example of an entirely network driven rhythm in a model of biophysical Hodgkin-Huxley model neurons. When increasing the intrinsic neuronal excitability of the neurons in the 3-neuron circuit modeled (a to c), the heteroclinic orbit underlying the rhythmic bursting becomes attracting, leading to an infinite slowdown of bursting as the trajectory of the system approaches it (c). The corresponding phase space picture in terms of the synaptic activation (which can be used as a proxy for firing rate) is shown in d). The trajectory starts in the green point and then approaches the stable heteroclinic orbit. Modified from Nowotny & Rabinovich (2007)

If the neurons can exhibit both intrinsic bursting and tonic spiking activity, network-induced bursting and pacemaker-type bursting dynamics may coexist and interact. Numerical experiments reveal at least two types of dynamics resulting from the interaction of intrinsic and network mechanisms.

When the neurons are hyperpolarized, network and intrinsic burst generation interact (cooperate) in forming network oscillations. Bursting is dominantly characterized by post-inhibitory rebound (PIR) and spontaneous burst termination of the neurons. Interestingly, the cooperation of network and intrinsic bursting mechanisms leads to bi-stability: A clockwise bursting sequence and an anti-clockwise bursting sequence coexist and are both stable. This bistability exists for a wide range of coupling strengths. Figure 5 shows an example of this phenomenon. In the clockwise bursting sequence  $1 \rightarrow 2 \rightarrow 3$ , the less

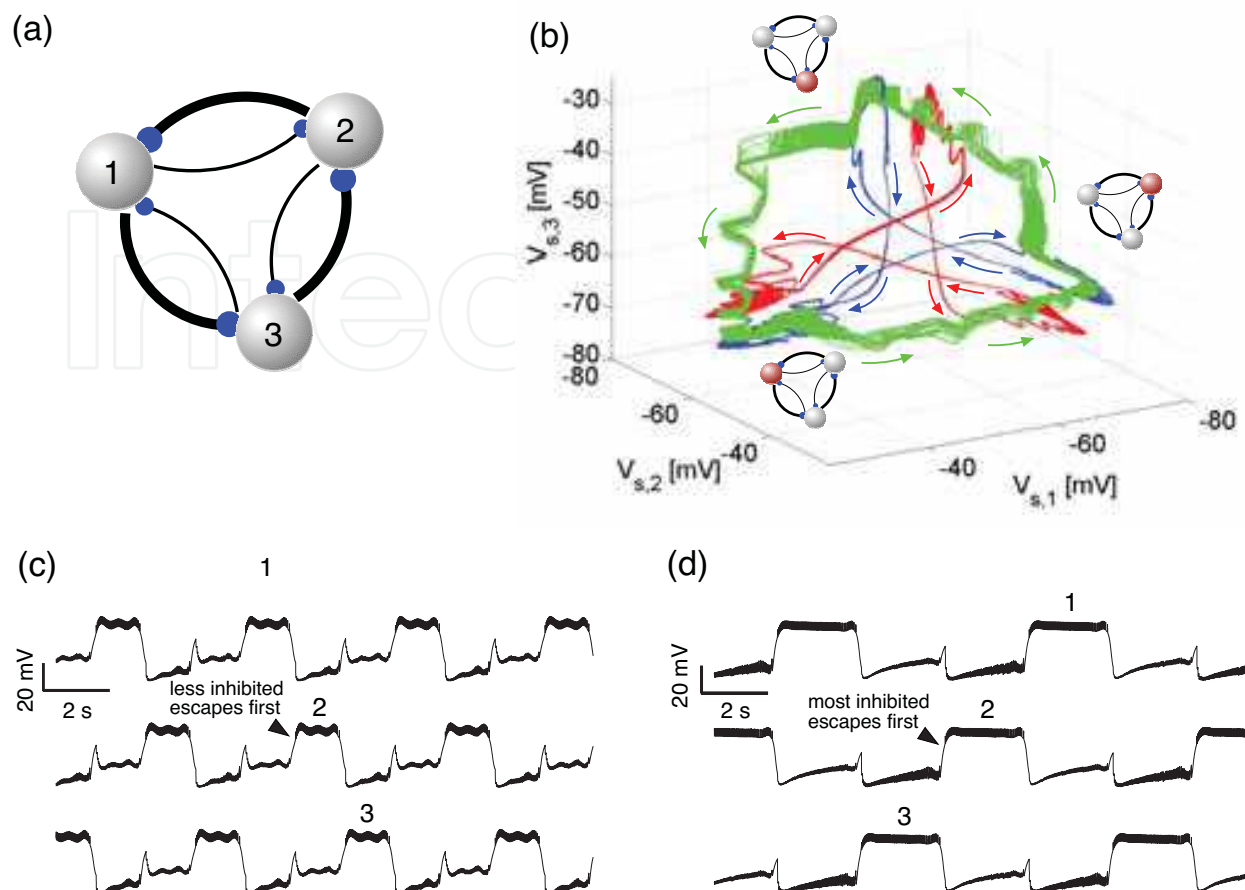


Fig. 5. A bifurcation towards bistability appears as a function of the “strength” of intrinsic bursting. A) face portraits of two co-existing attractors for strong bursting, *i.e.* for short bursts, ( $I_{DC} = -6$  nA): Sequences 1 → 2 → 3 (blue) and 3 → 2 → 1 (red) are both stable limit cycles. At weaker bursting, *i.e.* for long intrinsic bursts ( $I_{DC} = -1.0$  nA) only a 1 → 2 → 3 sequence exists (green). B) Example time series data for the 1 → 2 → 3 (top) and 3 → 2 → 1 sequence (bottom). Note how the less inhibited neuron escapes from inhibition first in the former and the more inhibited neuron escapes first in the latter. Modified from (Ivanchenko et al., 2008)

inhibited neuron escapes first from inhibition and continues the cycle (Fig. 5c). In the other case, the most inhibited neuron escapes first due to PIR and the sequence is counter-clockwise, 3 → 2 → 1 (Fig. 5d).

With decreasing intrinsic hyperpolarization of the neurons, the system undergoes a bifurcation towards mono-stability, where the network mechanism of burst generation persists, leading to a single attractor of clock-wise bursting (green trace in Fig. 5b). Intuitively, we can understand this transition as a transition of the neurons from strong bursters with strong PIR to weak bursters with long bursts and short, comparatively weak, hyperpolarization episodes. Consistently with this interpretation the bifurcation towards mono-stability occurs approximately at the point where the length of the intrinsic bursts of the neurons starts to exceed the duration of bursts in the network. With respect to the network dynamics, the neurons then act essentially like tonically spiking neurons.

With this model we are now also able to address some additional questions: i) What are the characteristics of the hybrid pacemaker-network mechanisms of bursting in the elementary

network? ii) What combination of neural circuit parameters, e.g., synaptic strengths or length of bursts, control the qualitative changes of the rhythmic patterns? iii) Do the concurrent mechanisms provide robustness and flexibility to the motif network, i.e., the ability to generate input-specific but reproducible responses under the action of an informational signal?

In the monostable regime of long intrinsic bursts the network activity is based on a competitive interaction of neurons that essentially restructures (shortens) the bursts, when inhibition strengthens. This interaction yields the unique bursting pattern, with characteristics that sensitively depend upon the level of inhibition (as with a pure network mechanism of burst generation).

Short intrinsic bursts on the other hand allow cooperative network oscillations, in which inhibitory interactions promote subsequent activity in inhibited neurons by PIR, in addition to the competition scenario. This leads to explained bistability of bursting patterns. Two parameters control the emergence of bistability: the asymmetry of reciprocal inhibition and the length of intrinsic bursts. Because of the interaction of intrinsic and synaptic dynamics both types of bursting patterns are highly robust, i.e., even if one of the neurons is changed to a tonic spiking regime, the other two neurons make it resume bursting and produce almost the same network patterns as if all neurons are identical (Ivanchenko et al., 2008). The hybrid pacemaker-network bursting does show a well-pronounced flexibility as well. The level of DC-input to the cells (interpreted as their intrinsic excitability) and synaptic plasticity can make the circuit switch between bistability and monostability, and modulating the overall synaptic strength can change the characteristics of bursting on a large scale.

Thus the hybrid pacemaker-network mechanism has modes of cooperation or of competition between the cellular and network dynamics and demonstrates both robustness (stability of the produced patterns) and flexibility (the ability to produce different patterns in response to appropriate stimuli) concurrently. The consequence of cooperation or competition is the bistability or monostability of spatio-temporal bursting patterns, and the decisive factors for either cooperation or competition are the parameters underlying intrinsic bursting. The other basic control parameter to switch between cooperation and competition is the asymmetry of coupling. Surprisingly it has been found that bistability only disappears for strong asymmetry, which suggests that comparatively weak background synaptic interactions could still qualitatively change the overall network dynamics and give rise to new bursting patterns and therefore cannot be neglected *a priori*.

### 3. Oscillatory motifs interaction

In complex hierarchical neural systems like the brain the oscillatory motifs that we have considered so far can play the role of individual dynamical agents. The cooperation and competition between them are the origin of many phenomena observed in the brain such as synchronization, low frequency oscillations, chaotic modulation of brain rhythms and so on.

#### 3.1 Motifs activity clustering and synchronization.

EEG recordings of brain activity exhibit multiple frequency peaks or rhythms in the range from  $< 1$  Hz, up to  $> 100$  Hz. These rhythms are able to synchronize with each other even when they have very different frequencies (Roopun et al., 2008). The functional roles played by these synchronized neuronal oscillations vary widely – synchronized rhythms can

facilitate synaptic plasticity (Buzsaki & Draguhn, 2004), correlate with attention (Womelsdorf et al., 2006), allow perceptual binding (Lachaux et al., 2005), and are involved in many others mechanisms (Palva & Palva, 2007). Recently, (Canolty et al., 2006) have observed robust coupling between the high- and low-frequency bands of ongoing electrical activity in the human brain. In particular, they indicated that the phase of the low-frequency theta (4 to 8 Hz) rhythm modulates the power in the high gamma (80 to 150 Hz) band of the electrocorticogram. The dynamical origin of such an interaction between rhythms with frequency ratios on the order of 15 – 20 is still unclear. We propose that the mechanism underlying this extraordinary phenomenon may be related to the heteroclinic modulation instability that we discussed above. It is well known that interneurons are able to cooperate in distinct local inhibitory networks (motifs) that are well-suited for generating synchronous gamma frequency rhythmic activity in the cortex (Whittington & Traub, 2003; Buzsaki, 2006). Because of the synchronization, such inhibitory motifs form clusters that compete with each other through slow inhibitory interaction. Thus, it is reasonable to hypothesize that the low frequency theta rhythm is a result of cyclic competition of different “theta clusters”. As a result of such a competition the power of gamma oscillations has to be strongly modulated by the rhythmic slow switching, i.e., the low frequency theta rhythm.

Another problem that is related to this subject is the synchronization of different low frequency theta-motifs by high frequency global brain rhythms. The existence of this type of synchronization supports the popular explanation of long-range coordination of distinct brain region’s activities (see (Fries, 2005) for review).

To illustrate the dynamical origin of such disparate-frequency synchronization we suppose that the theta rhythm is generated by WLC motifs and that different theta-motifs have no other interactions except for a joint external oscillatory field. In this case we can focus the analysis on the entrainment of the oscillations of one motif under the action of an oscillating external field.

The results of modeling the equations

$$\dot{a}_i = a_i \left[ 1 - \left( a_i + \sum_{j \neq i}^N \rho_{ij} a_j \right) + \xi(t) \right] + \gamma \varphi_i(\omega_f t, a_i), \quad (4)$$

where  $a_i(t) \geq 0$  represents the rate of the neural activity of the  $i$ th neural pool in the motif,  $0 < \rho_{ij} < 1$ ,  $\rho_{ii} = 1$  is an inhibitory connectivity matrix,  $\varphi_i(\omega t, a_i) \geq 0$  is a periodic function with period  $T = 2\pi/\omega$ ,  $\xi(t)$  is Gaussian white noise, and  $\gamma \ll 1$  is the coupling to the external field, are illustrated in Fig. 6.

Similarly, when considering a motif of spiking H-H type neurons coupled asymmetrically with inhibitory synapses, we observe wide areas of synchronization to an external oscillation continuing to very high frequency ratios (see Fig. 7). Surprisingly, this subharmonic synchronization already appears for fairly weak oscillatory drive, and even if only one of the neurons in the network is driven by it.

### 3.2 Chaotically modulated ordered sequences.

A related, but at first sight seemingly different, phenomenon is the emergence of reproducible but irregularly timed (chaotically modulated) sequences that have been proposed to underlie the chaotic hunting patterns by the marine mollusk *Clione* (Varona et al., 2002). In this work it was suggested, that the statocyst network, a small inhibitory micro-

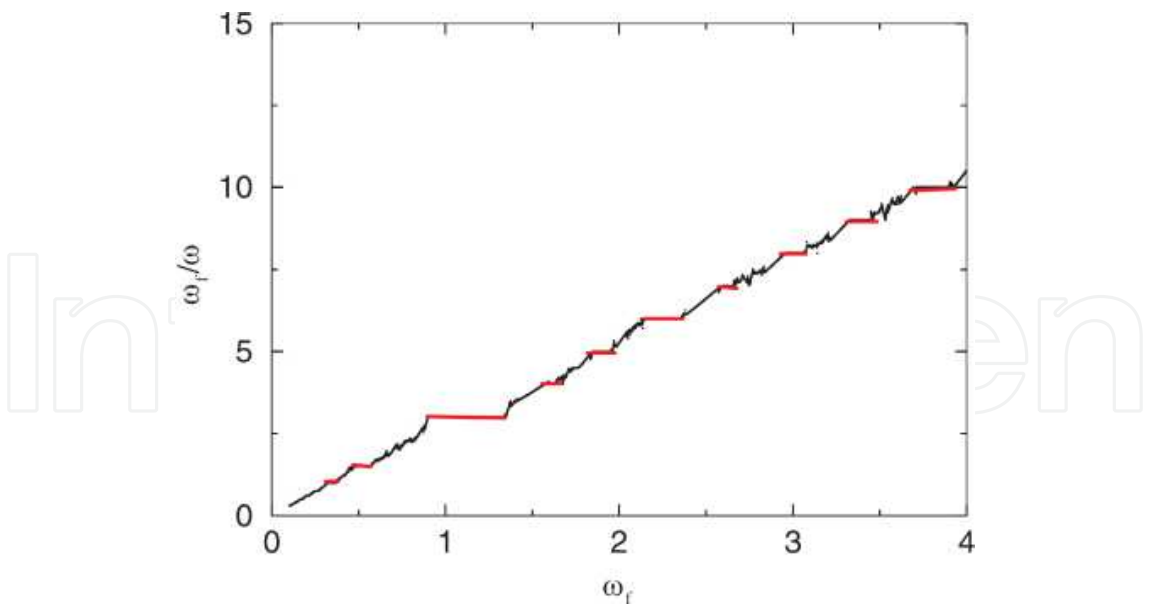


Fig. 6. Devil’s Staircase and bands of heteroclinic synchronization between low- and highfrequency oscillations. Modified from (Rabinovich, Huerta & Afraimovich, 2006)

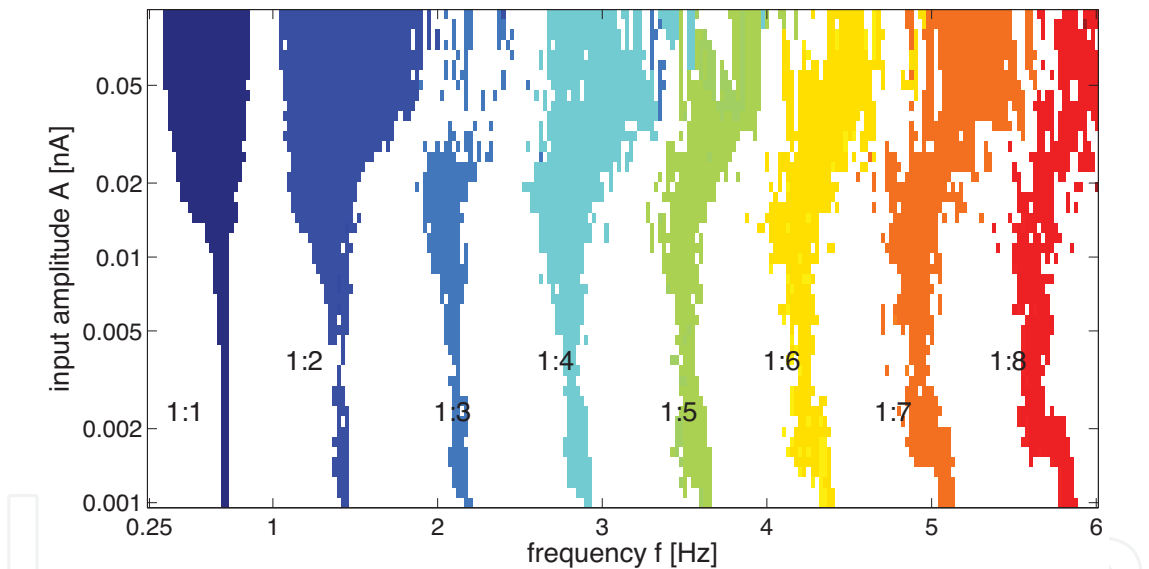


Fig. 7. Arnold tongues for a network of Hodgkin-Huxley model neurons. One of the neurons received the negative part of a sinusoidal external input. The oscillation frequency of the circuit was measured as the inverse of the average burst to burst period of all three neurons.

circuit in the brain of *Clione* that normally is used to balance the mollusk’s body position, is driven by a global excitatory drive from the “hunting neuron” whenever the mollusk senses the vicinity of its prey. This global excitation causes the network of the statocyst receptor cells (SRCs) to generate a complex output due to the intrinsic network dynamics (winnerless competition). This output is directed to the cerebral ganglia to participate in forming a search motor program. The theoretical validity of this hypothesis was demonstrated in the model study of Varona et al. (2002). It was found that a simple network formed by neuron-like elements with non-reciprocal inhibitory connections generated a complex switching



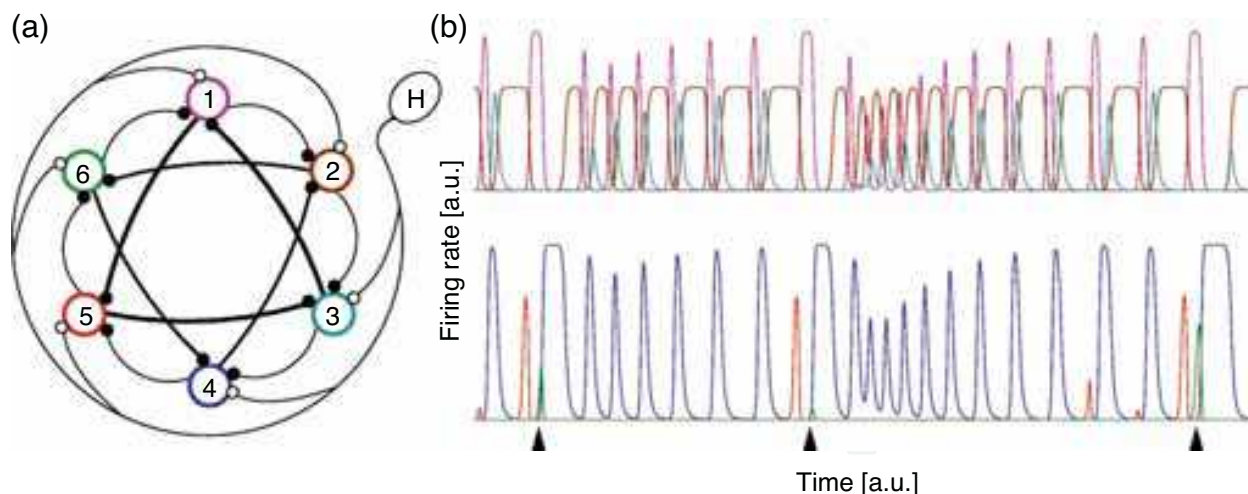


Fig. 8. Model for the statocyst network dynamics. A: architecture of the model network: color circles represent 6 model receptor neurons (MSRCs), and k circles represent inhibitory connections; thicker traces mean stronger connections. CHunINs are represented by H, and excitatory connections to the MSRCs are depicted with small white circles. B: firing rates of the MSRCs induced by activating the model CHunIN (H). Activities of the 1st MSRCs (units 1-6 in A) are shown in the top panel; the bottom panel corresponds to the activity of units 4-6; the colors used correspond to the colors of MSRCs shown in A. Arrows show an example of the coordinated activation among units even when the neurons are silent for a long period. Firing rates and time scale are arbitrary. Modified from (Levi et al., 2004)

activity in response to the excitatory input (H in Fig. 8), mimicking the effect of the *Clione* hunting interneurons (CHunINs). The excitation from the hunting neuron in the model was only used to trigger the activation of the receptor network dynamics. The model CHunIN activity did not require any temporal structure to produce the switching dynamics. In addition, the model showed that such a network can produce an ordered pattern of activation in otherwise irregular activity. This is a desirable feature to organize a complex but coordinated motion. The known anatomical connections suggest that the statocyst output can be reflected, at least partly, in the activity of tail motoneurons. Therefore, the model results are in correspondence with results obtained in electrophysiological experiments (Levi et al., 2004; 2005).

#### 4. Neuronal mass network oscillations

The execution of cognitive functions and information processing in the brain in general are largely based on dynamic interactions within a complex network of neurons. Neuronal mass modeling is one of the approaches that play an important role in investigating these processes. It can, in contrast to single neuron activity, be supported by non-invasive measurements such as EEG, MEG and fMRI. The analysis of the dynamics of interconnected neural mass networks can help to understand the origin of some brain activity and to find the relationship of it with brain measurements and psychological functions. Below we illustrate the phenomenon of emergent network rhythms in systems with random excitatory-inhibitory synaptic connections based on the Wilson-Cowan model of excitatory and inhibitory neuronal mass interaction. The Wilson-Cowan formalism (Wilson & Cowan, 1972; 1973) can be reduced to the following equations:

$$\mu \frac{\partial E(x,t)}{\partial t} = -E(x,t) + (1 - rE(x,t))\mathcal{L}_e \left( \int E(y,t)w_{ee}(y,x)dy - \int I(y,t)w_{ei}(y,x)dy + S_e(x,t) \right), \quad (5)$$

$$\mu \frac{\partial I(x,t)}{\partial t} = -I(x,t) + (1 - rI(x,t))\mathcal{L}_i \left( \int E(y,t)w_{ie}(y,x)dy - \int I(y,t)w_{ii}(y,x)dy + S_i(x,t) \right), \quad (6)$$

where  $E(x, t)$  and  $I(x, t)$  are the proportions of firing neurons in the excitatory and inhibitory populations, the coordinate  $x$  is a continuous variable that represents the position in the cortical surface,  $w_{ee}$ ,  $w_{ei}$ ,  $w_{ie}$ , and  $w_{ii}$  are the connectivity weights, and  $S_e$  and  $S_i$  are external inputs to the excitatory and inhibitory populations, respectively. The gain functions  $\mathcal{L}_e$  and  $\mathcal{L}_i$  reflect the expected proportions of excitatory and inhibitory neurons receiving at least threshold excitation per unit of time. One subtle trick used in the derivation of this model is that the membrane integration time is introduced through synaptic connections. The model expressed in this form attempts to eliminate the uncertainty of single neurons by grouping them according to those with reliable common responses. We are still left with the problem of what to expect in a network of neuronal masses connected randomly to each other.

In a random network of excitatory and inhibitory neurons, it is not uncommon to find oscillatory activity (Jin & Seung, 2002; Huerta & Rabinovich, 2004). Huerta & Rabinovich (2004) showed, using the Wilson-Cowan formalism, that periodic sequential activity, i.e., limit cycles, is more likely to be found in regions of the control parameter space where inhibitory and excitatory synapses are slightly out of balance. They have analyzed the Wilson-Cowan model in the form

$$\mu \frac{dx_i(t)}{dt} = \Theta \left( \sum_{j=1}^{N_E} w_{ij}^{EE} x_j(t) - \sum_{j=1}^{N_I} w_{ij}^{EI} y_j(t) + S_i^E \right) - x_i(t), \quad (7)$$

$$\mu \frac{dy_i(t)}{dt} = \Theta \left( \sum_{j=1}^{N_E} w_{ij}^{IE} x_j(t) - \sum_{j=1}^{N_I} w_{ij}^{II} y_j(t) + S_i^I \right) - y_i(t), \quad (8)$$

where  $x_i(t)$  and  $y_i(t)$  represent the fractions of active neurons in cluster  $i$  of the excitatory and inhibitory populations, respectively. The numbers of excitatory and inhibitory clusters are  $N_E$  and  $N_I$ . The labels  $E$  and  $I$  are used to denote quantities associated with the excitatory or inhibitory populations, respectively. The external inputs  $S_{E,I}$  are instantaneous kicks applied to a fraction of the total population at time zero. The gain function is  $\Theta(z) = (\tanh((z-b)/\sigma) + 1)/2$ , with a threshold  $b = 0.1$  below the excitatory and inhibitory synaptic strength of a single connection. Clusters are taken to have very sharp thresholds of excitability by choosing  $\sigma = 0.01$ . The time scale is set to  $\mu = 10$  ms as originally done by Wilson & Cowan (1972). The connectivity matrices  $w_{ij}^{XY}$  have entries drawn from a Bernoulli process (Huerta & Rabinovich, 2004). The main control parameters in this problem are the probability of connections from population to population.

Now we can answer the important question: What kind of activity can a network with many neurons and random connections produce? Intuition suggests that the answer has to be complex multidimensional dynamics. However, this is not the case. The results presented in Fig. 9 tell us that most observable stimulus-dependent dynamics are more simple and reproducible: periodic dynamics, transient dynamics, or low dimensional chaos.

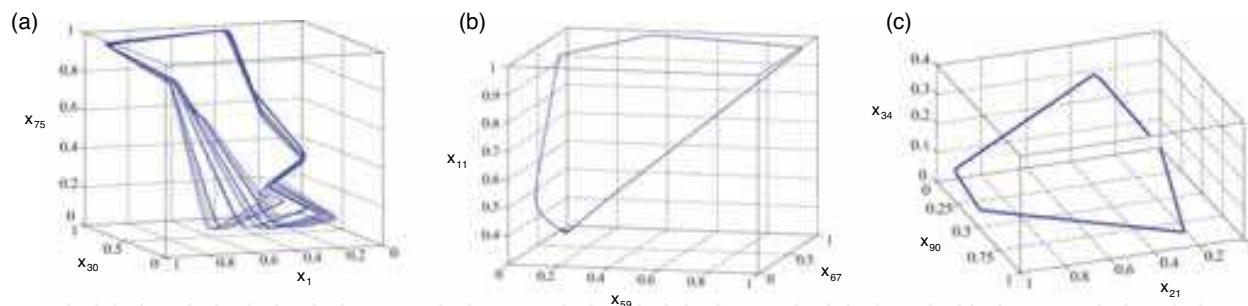


Fig. 9. Three-dimensional projections of simulations of random networks of 200 neurons. For illustrative purposes we show three types of dynamics that can be generated by a random network: a) chaos, b) limit cycle, both regimes in the areas of parameter space that are close to balance and c) transient dynamics far from balance of excitatory-inhibitory connections. Modified from (Rabinovich, Varona, Selverston & Abarbanel, 2006)

### 5. Mental mode network: Low frequency (< 0.1 Hz) rhythm generation

Now let us consider the spontaneous rhythmic dynamics of mental modes in a stationary environment where the brain is not engaged in a particular cognitive function, i.e., the resting-state brain dynamics. Mental modes have been introduced in (Rabinovich & Muezzinoglu, 2010) in the following way: The cognitive cooperative activity at time  $t$  can be represented as  $\sum_{i=1}^N A_i(t)V(i)$ , where  $V(i)$  is a fixed distributed neuronal set that forms the  $i$ -th cognitive mode, and  $A_i(t) \geq 0$  is its level of activity, in particular, the average intensity of all voxels covering the spatial pattern  $U(i)$  in an fMRI image at time  $t$ . Some of the cognitive modes can be responsible for the interaction with emotion, i.e., valence, arousal and generation of any given coping strategy (see also (Damasio, 1994)). The number  $N$  of these cognitive modes depends on the level of detail that is necessary to describe the particular brain state. Emotional activity is represented in the same way,  $\sum_{i=1}^M B_i(t)U(i)$ , where  $B_i(t) \geq 0$  are dynamical variables and  $U(i)$  is the structure of the  $i$ th emotional mode. The ensemble of emotional modes includes both positive and negative emotions in the model. Resources are represented in a similar manner.

*Mental modes competition* – Describing the interaction between mental modes, specifically cognitive and emotional modes that compete for the mental resources (memory, attention and so on), Rabinovich & Muezzinoglu (2010) have suggested a model of mental mode dynamics. This model is built for the variables,  $A_i(t)$ ,  $B_i(t)$ , and  $R_i(t)$ , which characterize mental resources, according to

$$\tau_A^i \frac{d}{dt} A_i(t) = A_i(t) \left( \sigma_i(S, B, R_A) - \sum_{j=1}^N \rho_{ij} A_j(t) \right) + A_i(t) \eta_A(t), \quad i = 1, \dots, N \quad (9)$$

$$\tau_B^i \frac{d}{dt} B_i(t) = B_i(t) \left( \zeta_i(S, A, R_B) - \sum_{j=1}^M \xi_{ij} B_j(t) \right) + B_i(t) \eta_B(t), \quad i = 1, \dots, M \quad (10)$$

$$\theta_A^i \frac{d}{dt} R_A^i(t) = R_A^i(t) \left( \sum_{j=1}^N A_j(t) - \sum_{j=1}^{K_A} R_A^j(t) - \phi_A \sum_{j=1}^{K_B} R_B^j(t) + d_A(t) \right), \quad i = 1, \dots, K_A \quad (11)$$

$$\theta_B^i \frac{d}{dt} R_B^i(t) = R_B^i(t) \left( \sum_{j=1}^M B_j(t) - \sum_{j=1}^{K_B} R_B^j(t) - \phi_B \sum_{j=1}^{K_A} R_A^j(t) + d_B(t) \right), \quad i = 1, \dots, K_B \quad (12)$$

As the authors proposed, this model reflects mutual inhibition and excitation within and among the three sets of modes (cognitive, emotional and resources). These modes depend on the external inputs through parameter  $S$  (e.g., stress, cognitive load, physical state of the body). Characteristic times of the cognitive and emotional activities are  $\tau_A$  and  $\tau_B$ , respectively. The variables  $R_A^i$  and  $R_B^i$  characterize the  $K_A$  and  $K_B$  resource items that are allocated to cognition and emotion, respectively. The vectors  $R_A$  and  $R_B$  are the collections of these items that gate the increments of the cognitive and emotional modes in competition. The characteristic times  $\theta$  of the different resources may vary. The coefficients  $\phi_A$  and  $\phi_B$  determine the level of competition between cognition and emotion for these resources. Each process is open to the multiplicative noise denoted by the  $\eta$  and  $d$  terms in the equations. We have chosen the control parameters of the model (9)-(12) in the area of the control parameter space where the basic dynamics of both cognitive and emotional modes

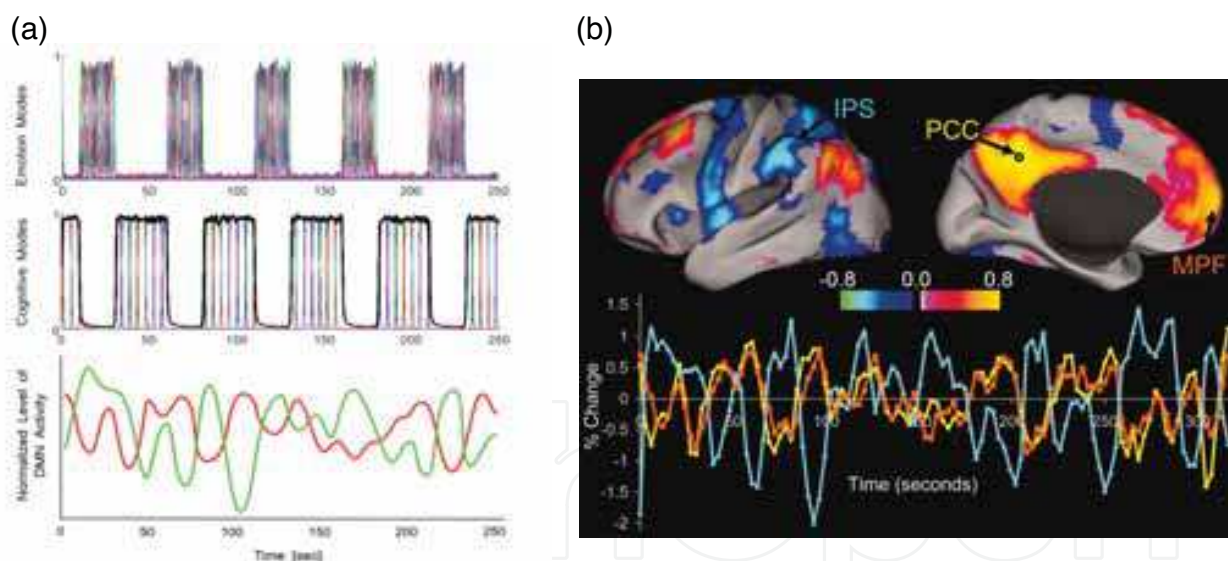


Fig. 10. Anti-phase Low-Frequency Oscillation of mental activity in the resting state (no external stimuli) is a result of two groups of default modes competition – modulation instability (a), modified from Rabinovich et al. (2010). The black envelope on the middle plot (a) is the total cognitive activity as predicted by the model. Its competition with the emotion modes (top row) results in a pulsation as observed in many EEG and fMRI studies. The bottom figure, reconstructed based on the data presented in (b), adapted from Fox et al. (2005), shows one such observation in the brain's resting state. (The resting state is related to the dynamics of the default-mode network (DMN), which is a set of specific brain regions whose activity is predominant during the resting state (Ben-Simon et al., 2008)).



demonstrate simple rhythmic activity (oscillations with the characteristic time of about 2 – 3 s). Such “independent” emotional and cognitive activity has been observed during weak competition. When the competition becomes larger than a critical value, this simple rhythmic activity becomes unstable due to a modulation instability, whereby a stable limit cycle appears on the phase plane of the mean activity  $\tilde{A}(t) = \frac{1}{N} \sum_{i=1}^N A_i$  and  $\tilde{B}(t) = \frac{1}{M} \sum_{i=1}^M B_i$ . This modulation instability leads to a stable LFO, as shown in Fig. 10 ( $S$  is constant and  $N = M = 5$  in the model (9)-(12)). The time-averaged oscillogram indicates that the observed robust modulation process is close to the quasi-periodic LFO. LFOs represent a fundamental component of brain activity. In particular, resting state fMRI measures show stable properties of LFO (see Fig. 10), the nature of which is only beginning to be uncovered and is producing numerous debates. For example, the LFO fluctuations observed with fMRI are not the same as the underlying neuronal fluctuations, because they have been passed through a hemodynamic response function. LFOs observed in fMRI could therefore simply be due to the band-pass filtering effect of this hemodynamic response function. However, some data (Tomasi & Volkow, 2010; Lörincz et al., 2009; Taylor et al., 2009; Buckner, 2010) support the hypothesis that LFOs are correlated with the network activity, i.e., the cooperative dynamics of network modes (e.g. due to their modulation or synchronization). The modulation instability that has been observed in the discussed computer experiments suggests a plausible dynamical origin of low frequency mental mode dynamics in brain resting states.

## 6. Conclusion

Integrating the results that have been discussed in this chapter, we can formulate some general statement, which sounds trivial enough: interactions between pacemaker and network mechanisms of rhythmic activity in neural systems are very diverse at all levels of the neuronal hierarchy. In complex systems, the role of the pacemaker can be played by neuronal clusters that are able to synchronize complex spatio-temporal patterns. However, what we can say more or less definitely is the following: *Low frequency oscillations* in complex systems, including the brain, are usually the result of cooperative activity of many neurons, brain centers, or modes. And, vice versa, (not necessary rhythmic) *fast switching between different states* is, as a rule, the result of activity of individual neurons. A recent report of Li et al. (2009) supports this point of view. In this study the authors showed that repetitive high-frequency bursts in a single cortical neuron of a rat could trigger a switch between the cortical states resembling slow-wave and rapid-eye-movement sleep.

## 7. References

- Afraimovich, V. S., Zhigulin, V. P. & Rabinovich, M. I. (2004). On the origin of reproducible sequential activity in neural circuits., *Chaos* 14(4): 1123–1129.  
URL: <http://dx.doi.org/10.1063/1.1819625>
- Ben-Simon, E., Podlipsky, I., Arieli, A., Zhdanov, A. & Hendler, T. (2008). Never resting brain: simultaneous representation of two alpha related processes in humans., *PLoS One* 3(12): e3984.



- URL: <http://dx.doi.org/10.1371/journal.pone.0003984>
- Börger, C., Epstein, S. & Kopell, N. J. (2005). Background gamma rhythmicity and attention in cortical local circuits: a computational study., *Proc Natl Acad Sci U S A* 102(19): 7002–7007. URL: <http://dx.doi.org/10.1073/pnas.0502366102>
- Buckner, R. L. (2010). Human functional connectivity: new tools, unresolved questions., *Proc Natl Acad Sci U S A* 107(24): 10769–10770.  
URL: <http://dx.doi.org/10.1073/pnas.1005987107>
- Buono, P.-L., Golubitsky, M. & Palacios, A. (2000). Heteroclinic cycles in rings of coupled cells, *Physica D: Nonlinear Phenomena* 143: 74–108.
- Buzsaki, G. (2006). *Rhythms of the Brain*, Oxford University Press, New York.
- Buzsaki, G. & Draguhn, A. (2004). Neuronal oscillations in cortical networks., *Science* 304(5679): 1926–1929.  
URL: <http://dx.doi.org/10.1126/science.1099745>
- Calabrese, R. L. (1995). Oscillation in motor pattern-generating networks., *Curr Opin Neurobiol* 5(6): 816–823.
- Calabrese, R. L. (1998). Cellular, synaptic, network, and modulatory mechanisms involved in rhythm generation., *Curr Opin Neurobiol* 8(6): 710–717.
- Canolty, R. T., Edwards, E., Dalal, S. S., Soltani, M., Nagarajan, S. S., Kirsch, H. E., Berger, M. S., Barbaro, N. M. & Knight, R. T. (2006). High gamma power is phase-locked to theta oscillations in human neocortex., *Science* 313(5793): 1626–1628.  
URL: <http://dx.doi.org/10.1126/science.1128115>
- Damasio, A. (1994). *Descartes' Error: Emotion, Reason and the Human Brain*, Putnam, New York.
- Fox, M. D., Snyder, A. Z., Vincent, J. L., Corbetta, M., Essen, D. C. V. & Raichle, M. E. (2005). The human brain is intrinsically organized into dynamic, anticorrelated functional networks., *Proc Natl Acad Sci U S A* 102(27): 9673–9678.  
URL: <http://dx.doi.org/10.1073/pnas.0504136102>
- Fries, P. (2005). A mechanism for cognitive dynamics: neuronal communication through neuronal coherence., *Trends Cogn Sci* 9(10): 474–480.  
URL: <http://dx.doi.org/10.1016/j.tics.2005.08.011>
- Golomb, D. & Ermentrout, G. B. (2002). Slow excitation supports propagation of slow pulses in networks of excitatory and inhibitory populations., *Phys Rev E Stat Nonlin Soft Matter Phys* 65(6 Pt 1): 061911.
- Huerta, R. & Rabinovich, M. (2004). Reproducible sequence generation in random neural ensembles., *Phys Rev Lett* 93(23): 238104.
- Ivanchenko, M. V., Nowotny, T., Selverston, A. I. & Rabinovich, M. I. (2008). Pacemaker and network mechanisms of rhythm generation: cooperation and competition., *J Theor Biol* 253(3): 452–461.  
URL: <http://dx.doi.org/10.1016/j.jtbi.2008.04.016>
- Jin, D. Z. & Seung, H. S. (2002). Fast computation with spikes in a recurrent neural network, *Phys. Rev. E* 65(5): 051922.
- Johnson, S. M., Wiegel, L. M. & Majewski, D. J. (2007). Are pacemaker properties required for respiratory rhythm generation in adult turtle brain stems in vitro?, *Am J Physiol Regul Integr Comp Physiol* 293(2): R901–R910.

- URL: <http://dx.doi.org/10.1152/ajpregu.00912.2006>
- Komarov, M. A., Osipov, G. V., Suykens, J. A. K. & Rabinovich, M. I. (2009). Numerical studies of slow rhythms emergence in neural microcircuits: bifurcations and stability., *Chaos* 19(1): 015107.  
URL: <http://dx.doi.org/10.1063/1.3096412>
- Kopell, N., Börger, C., Pervouchine, D., Malerba, P. & Tort, A. (2005). Gamma and theta rhythms in biophysical models of hippocampal circuits, in V. Cutsuridis, S. Cobb, B. Graham & I. Vida (eds), *Hippocampal Microcircuits: A Computational Modeler's Resource Book*, Springer, New York, pp. 423–457.
- Kuznetsov, Y. (1998). *Elements of Applied Bifurcation Theory*, Vol. 112 of *Applied Mathematical Sciences*, Springer, New York.
- Lachaux, J.-P., George, N., Tallon-Baudry, C., Martinerie, J., Hugueville, L., Minotti, L., Kahane, P. & Renault, B. (2005). The many faces of the gamma band response to complex visual stimuli., *Neuroimage* 25(2): 491–501.  
URL: <http://dx.doi.org/10.1016/j.neuroimage.2004.11.052>
- Levi, R., Varona, P., Arshavsky, Y. I., Rabinovich, M. I. & Selverston, A. I. (2004). Dual sensory motor function for a molluscan statocyst network., *J Neurophysiol* 91(1): 336–345.  
URL: <http://dx.doi.org/10.1152/jn.00753.2003>
- Levi, R., Varona, P., Arshavsky, Y. I., Rabinovich, M. I. & Selverston, A. I. (2005). The role of sensory network dynamics in generating a motor program., *J Neurosci* 25(42): 9807–9815.  
URL: <http://dx.doi.org/10.1523/JNEUROSCI.2249-05.2005>
- Lewis, M. A., Etienne-Cummings, R., Hartmann, M. J., Xu, Z. R. & Cohen, A. H. (2003). An in silico central pattern generator: silicon oscillator, coupling, entrainment, and physical computation., *Biol Cybern* 88(2): 137–151.  
URL: <http://dx.doi.org/10.1007/s00422-002-0365-7>
- Li, C.-Y. T., Poo, M.-M. & Dan, Y. (2009). Burst spiking of a single cortical neuron modifies global brain state., *Science* 324(5927): 643–646.  
URL: <http://dx.doi.org/10.1126/science.1169957>
- Lörincz, M. L., Geall, F., Bao, Y., Crunelli, V. & Hughes, S.W. (2009). ATP-dependent infra-slow (<0.1 Hz) oscillations in thalamic networks., *PLoS One* 4(2): e4447.  
URL: <http://dx.doi.org/10.1371/journal.pone.0004447>
- Machens, C. K., Romo, R. & Brody, C. D. (2005). Flexible control of mutual inhibition: a neural model of two-interval discrimination., *Science* 307(5712): 1121–1124.  
URL: <http://dx.doi.org/10.1126/science.1104171>
- Mancilla, J. G., Lewis, T. J., Pinto, D. J., Rinzel, J. & Connors, B. W. (2007). Synchronization of electrically coupled pairs of inhibitory interneurons in neocortex., *J Neurosci* 27(8): 2058–2073.  
URL: <http://dx.doi.org/10.1523/JNEUROSCI.2715-06.2007>
- Milo, R., Shen-Orr, S., Itzkovitz, S., Kashtan, N., Chklovskii, D. & Alon, U. (2002). Network motifs: simple building blocks of complex networks., *Science* 298(5594): 824–827.  
URL: <http://dx.doi.org/10.1126/science.298.5594.824>

- Nowotny, T., Levi, R. & Selverston, A. I. (2008). Probing the dynamics of identified neurons with a data-driven modeling approach., *PLoS One* 3(7): e2627.  
URL: <http://dx.doi.org/10.1371/journal.pone.0002627>
- Nowotny, T. & Rabinovich, M. I. (2007). Dynamical origin of independent spiking and bursting activity in neural microcircuits., *Phys Rev Lett* 98(12): 128106.
- Palva, S. & Palva, J. M. (2007). New vistas for alpha-frequency band oscillations., *Trends Neurosci* 30(4): 150–158.  
URL: <http://dx.doi.org/10.1016/j.tins.2007.02.001>
- Rabinovich, M. I., Huerta, R. & Afraimovich, V. (2006). Dynamics of sequential decision making., *Phys Rev Lett* 97(18): 188103.
- Rabinovich, M. I., Huerta, R. & Varona, P. (2006). Heteroclinic synchronization: ultrasubharmonic locking., *Phys Rev Lett* 96(1): 014101.
- Rabinovich, M. I., Huerta, R., Varona, P. & Afraimovich, V. S. (2006). Generation and reshaping of sequences in neural systems., *Biol Cybern* 95(6): 519–536.  
URL: <http://dx.doi.org/10.1007/s00422-006-0121-5>
- Rabinovich, M. I., Huerta, R., Varona, P. & Afraimovich, V. S. (2008). Transient cognitive dynamics, metastability, and decision making., *PLoS Comput Biol* 4(5): e1000072.  
URL: <http://dx.doi.org/10.1371/journal.pcbi.1000072>
- Rabinovich, M. I., Huerta, R., Volkovskii, A., Abarbanel, H. D., Stopfer, M. & Laurent, G. (2000). Dynamical coding of sensory information with competitive networks., *J Physiol Paris* 94(5-6): 465–471.
- Rabinovich, M. I., Muezzinoglu, M. K., Strigo, I. & Bystritsky, A. (2010). Dynamical principles of emotion-cognition interaction: Mathematical images of mental disorders, *PLoS ONE* 5(9): e12547.  
URL: <http://dx.doi.org/10.1371/journal.pone.0012547>
- Rabinovich, M. I., Varona, P., Selverston, A. I. & Abarbanel, H. D. I. (2006). Dynamical principles in neuroscience, *Rev Mod Phys* 78: 1213–1265.
- Rabinovich, M. & Muezzinoglu, M. (2010). Nonlinear dynamics of the brain: emotion and cognition, *Physics-Uspekhi* 53(4): 357–372.
- Rabinovich, M., Volkovskii, A., Lecanda, P., Huerta, R., Abarbanel, H. D. & Laurent, G. (2001). Dynamical encoding by networks of competing neuron groups: winnerless competition., *Phys Rev Lett* 87(6): 068102.
- Roopun, A. K., Kramer, M. A., Carracedo, L. M., Kaiser, M., Davies, C. H., Traub, R. D., Kopell, N. J. & Whittington, M. A. (2008). Temporal interactions between cortical rhythms., *Front Neurosci* 2(2): 145–154.  
URL: <http://dx.doi.org/10.3389/neuro.01.034.2008>
- Rybak, I. A., Abdala, A. P. L., Markin, S. N., Paton, J. F. R. & Smith, J. C. (2007). Spatial organization and state-dependent mechanisms for respiratory rhythm and pattern generation., *Prog Brain Res* 165: 201–220.  
URL: [http://dx.doi.org/10.1016/S0079-6123\(06\)65013-9](http://dx.doi.org/10.1016/S0079-6123(06)65013-9)
- Rybak, I. A., Shevtsova, N. A., Paton, J. F. R., Pierrefiche, O., St-John, W. M. & Haji, A. (2004). Modelling respiratory rhythmogenesis: focus on phase switching mechanisms., *Adv Exp Med Biol* 551: 189–194.

- Silverston, A. I. & Miller, J. P. (1980). Mechanisms underlying pattern generation in lobster stomatogastric ganglion as determined by selective inactivation of identified neurons. i. pyloric system., *J Neurophysiol* 44(6): 1102–1121.
- Skinner, F. K., Kopell, N. & Marder, E. (1994). Mechanisms for oscillation and frequency control in reciprocally inhibitory model neural networks., *J ComputNeurosci* 1(1-2): 69–87.
- Skinner, F. K., Zhang, L., Velazquez, J. L. & Carlen, P. L. (1999). Bursting in inhibitory interneuronal networks: A role for gap-junctional coupling., *J Neurophysiol* 81(3): 1274–1283.
- Sohal, V. S., Pangratz-Fuehrer, S., Rudolph, U. & Huguenard, J. R. (2006). Intrinsic and synaptic dynamics interact to generate emergent patterns of rhythmic bursting in thalamocortical neurons., *J Neurosci* 26(16): 4247–4255.  
URL: <http://dx.doi.org/10.1523/JNEUROSCI.3812-05.2006>
- Sporns, O. & Kötter, R. (2004). Motifs in brain networks., *PLoS Biol* 2(11): e369.  
URL: <http://dx.doi.org/10.1371/journal.pbio.0020369>
- Taylor, K. S., Seminowicz, D. A. & Davis, K. D. (2009). Two systems of resting state connectivity between the insula and cingulate cortex., *Hum Brain Mapp* 30(9): 2731–2745.  
URL: <http://dx.doi.org/10.1002/hbm.20705>
- Tomasi, D. & Volkow, N. D. (2010). Functional connectivity density mapping., *Proc Natl Acad Sci U S A* 107(21): 9885–9890.  
URL: <http://dx.doi.org/10.1073/pnas.1001414107>
- Tong, F., Meng, M. & Blake, R. (2006). Neural bases of binocular rivalry., *Trends Cogn Sci* 10(11): 502–511.  
URL: <http://dx.doi.org/10.1016/j.tics.2006.09.003>
- Varona, P., Rabinovich, M. I., Silverston, A. I. & Arshavsky, Y. I. (2002). Winnerless competition between sensory neurons generates chaos: A possible mechanism for molluscan hunting behavior., *Chaos* 12(3): 672–677.  
URL: <http://dx.doi.org/10.1063/1.1498155>
- Wang, X. J. & Rinzel, J. (1993). Spindle rhythmicity in the reticularis thalami nucleus: synchronization among mutually inhibitory neurons., *Neuroscience* 53(4): 899–904.
- Whittington, M. A. & Traub, R. D. (2003). Interneuron diversity series: inhibitory interneurons and network oscillations in vitro., *Trends Neurosci* 26(12): 676–682.
- Whittington, M. A., Traub, R. D., Kopell, N., Ermentrout, B. & Buhl, E. H. (2000). Inhibition-based rhythms: experimental and mathematical observations on network dynamics., *Int J Psychophysiol* 38(3): 315–336.
- Wilson, H. R. & Cowan, J. D. (1972). Excitatory and inhibitory interactions in localized populations of model neurons., *Biophys J* 12(1): 1–24.  
URL: [http://dx.doi.org/10.1016/S0006-3495\(72\)86068-5](http://dx.doi.org/10.1016/S0006-3495(72)86068-5)
- Wilson, H. R. & Cowan, J. D. (1973). A mathematical theory of the functional dynamics of cortical and thalamic nervous tissue., *Kybernetik* 13(2): 55–80.
- Womelsdorf, T., Fries, P., Mitra, P. P. & Desimone, R. (2006). Gamma-band synchronization in visual cortex predicts speed of change detection., *Nature* 439(7077): 733–736.  
URL: <http://dx.doi.org/10.1038/nature04258>

Yuste, R., MacLean, J. N., Smith, J. & Lansner, A. (2005). The cortex as a central pattern generator., *Nat Rev Neurosci* 6(6): 477–483.

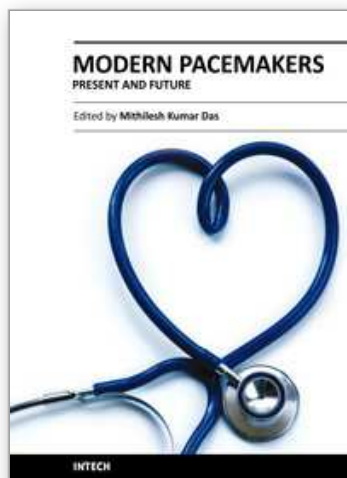
URL: <http://dx.doi.org/10.1038/nrn1686>

Zhigulin, V. P. (2004). Dynamical motifs: building blocks of complex dynamics in sparsely connected random networks., *Phys Rev Lett* 92(23): 238701.

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### **Modern Pacemakers - Present and Future**

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The book focuses upon clinical as well as engineering aspects of modern cardiac pacemakers. Modern pacemaker functions, implant techniques, various complications related to implant and complications during follow-up are covered. The issue of interaction between magnetic resonance imaging and pacemakers are well discussed. Chapters are also included discussing the role of pacemakers in congenital and acquired conduction disease. Apart from pacing for bradycardia, the role of pacemakers in cardiac resynchronization therapy has been an important aspect of management of advanced heart failure. The book provides an excellent overview of implantation techniques as well as benefits and limitations of cardiac resynchronization therapy. Pacemaker follow-up with remote monitoring is getting more and more acceptance in clinical practice; therefore, chapters related to various aspects of remote monitoring are also incorporated in the book. The current aspect of cardiac pacemaker physiology and role of cardiac ion channels, as well as the present and future of biopacemakers are included to glimpse into the future management of conduction system diseases. We have also included chapters regarding gut pacemakers as well as pacemaker mechanisms of neural networks. Therefore, the book covers the entire spectrum of modern pacemaker therapy including implant techniques, device related complications, interactions, limitations, and benefits (including the role of pacing role in heart failure), as well as future prospects of cardiac pacing.

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