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Front Waves of Chemical Reactions and Travelling Waves of Neural Activity

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Abstract

Travelling waves crossing the nervous networks at mesoscopic/macroscopic scales have been correlated with different brain functions, from long-term memory to visual stimuli. Here we investigate a feasible relationship between wave generation/propagation in recurrent nervous networks and a physical/chemical model, namely the Belousov–Zhabotinsky reaction (BZ). Since BZ's nonlinear, chaotic chemical process generates concentric/intersecting waves that closely resemble the diffusive nonlinear/chaotic oscillatory patterns crossing the nervous tissue, we aimed to investigate whether wave propagation of brain oscillations could be described in terms of BZ features. We compared experimentally detected oscillations during the spontaneous activity of the brain with BZ-like concentric waves simulated by a recently introduced artificial network. The observed overlap and agreement between simulated and measured oscillatory patterns suggests that changes in cortical areas' neural activity might be described in terms of a recognizable diffusion pattern. We describe biological plausibility, benefits and limits of our approach and discuss the relationship among BZ-like networks, Pandemonium-like architectures and the spontaneous activity of the brain.

Key Words: central nervous system, chaos, chemical reaction, spontaneous activity, BOLD activity, nonlinear dynamics

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Introduction

Travelling waves of neural activity, spontaneously generated by intrinsic circuits or evoked by external stimuli, cross the brain at single-area and whole-brain scales (Muller *et al.,* 2018; Zhang *et al.,*

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2018). These spatiotemporal cortical patterns have been correlated with a variety of mental functions, from long-term memory consolidation to processing of visual stimuli (**Figure 1**). It has been hypothesized that synchronous occurrence of neural oscillations in different neural populations might assist information transfer among these populations (Akam and Kullmann, 2010). A broad computational and mathematical literature on travelling waves in neural networks has been produced, focusing on theoretical mechanisms for wave spreading. Here we ask whether wave generation and propagation in recurrent nervous networks might be correlated with extant physical/chemical models. A chemical system termed Belousov–Zhabotinsky reaction (BZ), though an incomplete analogy to the cortical activity, provides a suggestive template for waves radiating from brain sub-areas. BZ describes an unusual, nonlinear chemical oscillator: in presence of bromine and an acid, concentric circles are effortlessly and incessantly produced in a Petri dish, giving rise to simultaneous, intersecting wave fronts which intermingle and/or reciprocally annihilate (**Figure 2A**). BZ models of noise-induced order have been used for chemical computations describing far from equilibrium nonlinear dynamics and chaotic evolution. BZ-like computational models rely on geometrically constrained excitable chemical mediums which make use of changes in reagents concentrations to transmit information. This approach has been proven useful in different contexts such as, e.g., image processing, Voronoi diagram, logical computations. Zhang et al. (2012) designed circuits that reproduce the typical oscillatory patterns of BZ. Their circuits consist of planar, geometrically constrained, binary adder chemical devices that perform not just two-bit, but also multi-bit logical computations. Sun and Zhao (2013) and Guo et al. (2014) further described how one-bit decoders can be extended through cascade methods to design two-bit, three-bit, or higher bit binary decoders.

BZ-like travelling waves can be used to investigate physical and/or biological phenomena: for example, they mimic the cardiac electrical waves and resemble the oscillations of certain bacterial colonies (Cincotti *et al.,* 2019). Here we tackle the BZ issue from the standpoint of the brain cortical activity: does a correlation exist between the configurations of BZ oscillations and brain waves? The answer could be positive, if we consider that the vibrations inside a BZ medium create a pattern of simultaneous and/or successive concentric waves across the surface that closely resemble the travelling waves produced in the cortex by the impact of afferent action potentials. Instead of precise zero-lag synchrony, a range of flexible phase relationships might produce waves of various shapes including plane, radial and spiral waves, and complex spatiotemporal patterns.

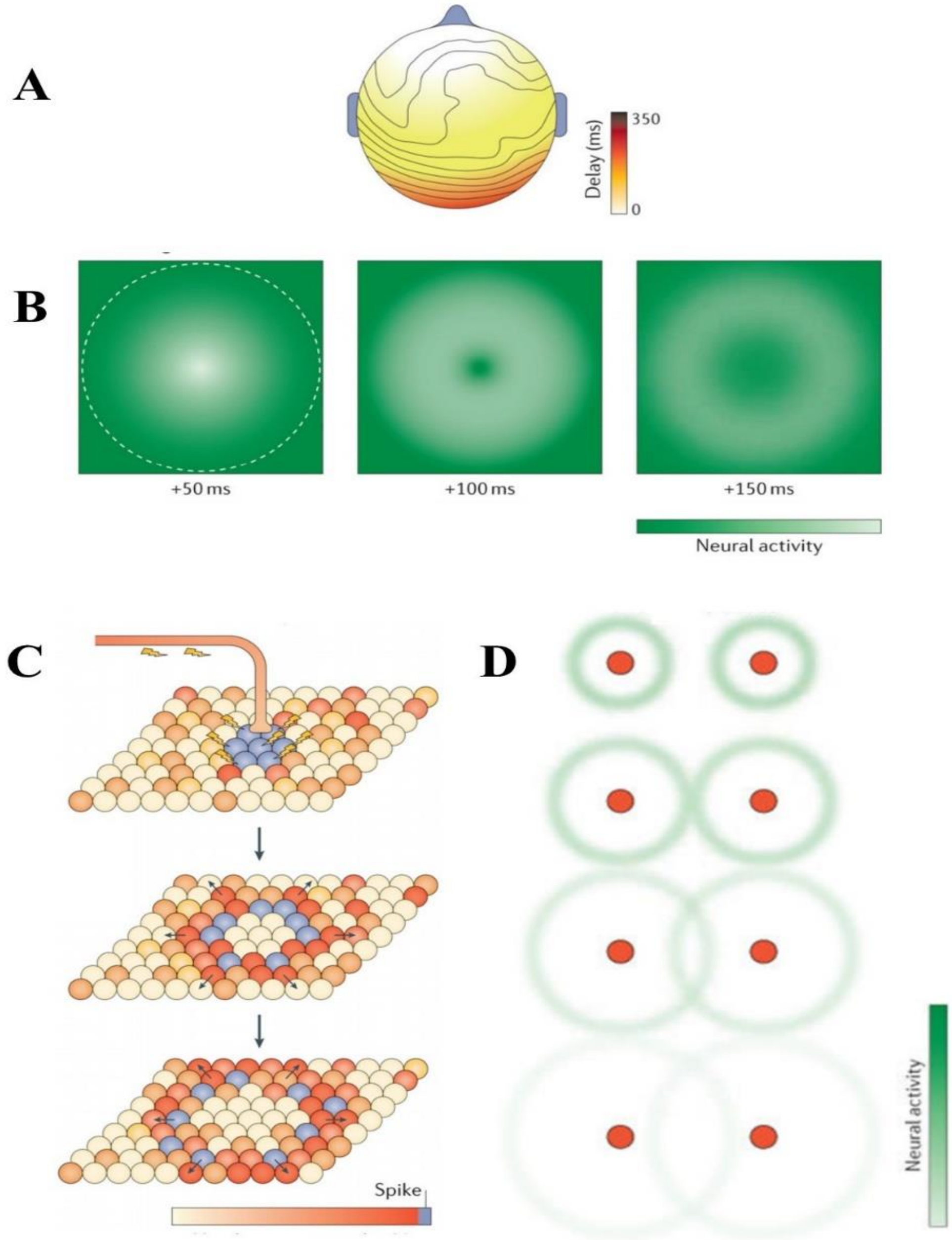


Figure 1. Examples of cortical travelling waves. **Figure 1A**. The slow oscillations of deep non-rapid-eye-movement sleep are reported in terms of a travelling wave moving globally from anterior to posterior regions (modified from Massimini et al. 2004). **Figure 1B**. A model for stimulus-evoked responses in the visual cortex. Within the response zone, the activity pattern might take two main forms: either stationary bumps of activity (not shown here) or travelling waves (illustrated in the picture). Modified from Muller et al. (2018). **Figure 1C**. Schematic model for wave generation in topographic networks of neurons with local random connections. Spheres represent neurons whose membrane potential is indicated by colour. In waking states, cortical networks with strong background display local stimulation that elicits waves weakly entraining neuronal spiking (Muller *et al.*, 2018). **Figure 1D**. Interaction between sparse, weakly interacting cortical waves. It has been hypothesized that such oscillations might generate a symmetric global wave field when passing through each other. Modified from Muller et al. (2018) and Perrard et al. (2016).

Brain activity has another common ground with BZ: both display oscillations characterized by chaotic features and self-organizing activity under the influence of specific stimuli (Fraiman and Chialvo, 2012; Zare and Grigolini, 2013; Qu *et al.,* 2014; Tozzi *et al.,* 2017); both exhibit "excitability", i.e., the sudden occurrence of patterns, such as the neural avalanches, emerging in an apparently quiescent medium (Tyukin *et al.,* 2019). Starting from these premises, we tested whether BZ-like mechanisms might underlie the oscillatory behavior of fMRI BOLD activation during spontaneous activity of the brain. To pursue our goal, we introduced a novel computational model of nervous activity, i.e., a BZ-like circuit that mimics the oscillations arising from single cortical subareas and propagating (non-homogeneously and non-ergodically) towards different cortical locations. We compared the simulated waves produced by our BZ network with available real neurodata and found that the propagation of nervous oscillations in the brain matches the propagation of the simulated waves generated by of our BZ-like circuit.

Materials and Methods

Our aim was to compare innovative artificial circuits simulating the typical BZ waves with the real patterns of oscillations extracted from fMRI movies of the spontaneous activity of the brain.

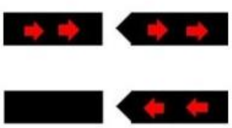
Previous circuits based on Belousov-Zhabotinsky reaction. In previous studies, BZ has been described in terms of circuits that reproduce the typical front waves and superimposing oscillatory patterns of this unusual chemical reaction (**Figure 2A**). For further details and the master equations, see Zhang et al. (2012); Sun and Zhao (2013); Guo et al. (2014). The basic unit of the circuit, termed binary adder unit (BAU), consists of simple straight-line boundaries. BAU was implemented with a number of tools, such as unidirectional transmission, T-shaped and cross-propagation structures (**Figures 2B-D**). Due to its geometrically constrained structure, BAU performs the addition of binary information without the need of ruling clocks or adjustments in parameters. Methodologies borrowed by adders building in digital circuits permits to couple single-bit BAUs and produce two-bit binary adders and, as the number of bits increases, more complex multi-bit binary decoders. The latter can be designed via nesting and cascade methods that link n-bit decoders ($n \geq 2$) with ($n - 1$)-bit decoders, so that every n-bit decoder includes the simpler structure of a ($n - 1$)-bit decoder. This iterative process produces both simple (One-way propagation, Osmotic propagation, Delayed propagation) and complex circuits (Adders, Memory, Decoders, Comparators). Simulations have demonstrated the feasibility of such a combinatory logical circuit able to convert binary information from n input lines to a maximum of $2n$ unique output lines (Guo *et al.,* 2014). Multi-bit digital comparators allow not just the assessment of two multi-bit binary numbers one bit after another, but also the use of the Boolean terms 0 and 1 to describe the results. In sum, quite simple basic units can be combined via special connection methods in network models that mimic the behavior of BZ concentric oscillations, making it possible to produce more elaborate computational functions.

Entering the brain activity: lag threads. High-dimensional structures with variable delay termed "lag threads" have been found in the brain during spontaneous activity, consisting of multiple, highly reproducible temporal sequences that propagate from one brain region to another. Mitra et al. (2015) suggested that the brain activity encompasses both single and multiple lag threads. We retrospectively evaluated video frames showing lag threads computed from real BOLD resting state rs-fMRI data. Data were extracted from 688 subjects (Harvard-MGH Brain Genomics Superstruct Project). We examined 54 images from four sets of movies (Threads 1, 2, 3 and 4) including transverse sections of the brain. The videos are freely-available: http://www.pnas.org/content/suppl/2015/03/24/1503960112.DCSupplemental.

Building the proper circuits. The next step was to build a BZ-like artificial circuit appropriate to describe real lag threads. Instead of the usual neural models such as McCulloch-Pitts Neurons, Hopfield networks and so on (Hopfield 1982; Tozzi *et al.,* 2016), we used a node-like structure especially designed for simulation of both single lag threads and the superposition of multiple lag threads. This novel network, rather different from the adder units, decoders and comparators portrayed in previous papers (Zhang *et al.,* 2012; Sun and Zhao, 2013), describes neuronal unities at different levels of observation, from the micro-to the macro-level. Indeed, a BZ-like neural unit (provided with input and output channels) may stand both for a large cortical area and for a small group of neurons.

To keep the model as simple as possible, the basic node-like structures (neuronal units) inspired by lag threads are rectangular ring channels equipped with input and output channels. The circuit permits different paths according to the temporal sequence of signals propagation in real threads. The number of inputs and outputs mimics the number of threads: e.g., **Figures 2B-C** show two inputs and two outputs channels.

To achieve the proper propagation sequence between nodes, we introduced one-way transmission structures:



where signals are unidirectional, e.g., they are allowed to travel just from left to right and not vice versa. The addition of unidirectional transmission structures to input channels prevents signal output through the input channel.

The very features of a basic BZ-like circuit suggest that two different paths may occur (Sun and Zhao, 2013):

a) signal transmission from inputs to outputs (**Figures 2B-C**).

b) signal annihilation when two front waves meet (**Figure 2D**).

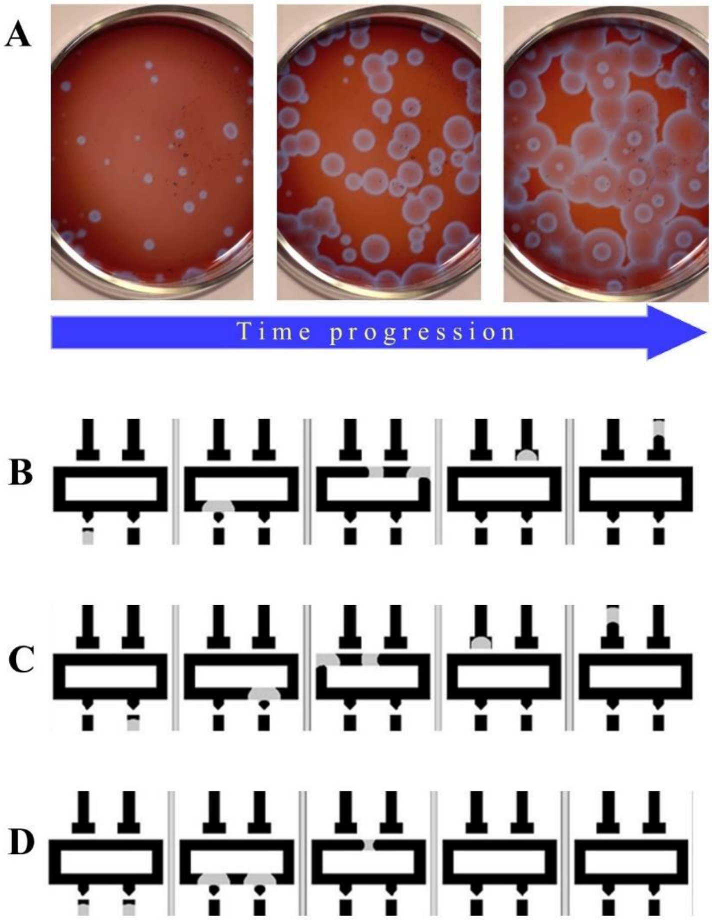


Figure 2. Comparison between travelling waves produced by chemical BZ and by one-bit digital comparators. **Figure 1A**: Two-dimensional BZ in a Petri dish. The typical configuration of wave sources produces circular and spiral oscillations, as shown in these frames modified from: https://www.youtube.com/watch?v=jRQAndvF4sM. Note how the temporal evolution of the numerous chemical wave fronts leads to their merging, superimposition or annihilation. **Figure 1B-D**: Three different possible patterns of wave propagation in basic one-bit digital comparators. **Figures 2B-C** show how a single wave propagating from a single input channel (bottom) is able to reach a single output channel (top) after a wave bifurcation. **Figure 1D** shows how two waves propagating from two different input channels are not able to reach the output channels, because their gathering leads to mutual annihilation.

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Simulations of BZ-like concentric patterns on brain-like templates. Once achieved a BZ-like network simulating lag threads, our aim was to assess whether the concentric oscillatory paths produced by our circuit could be superimposed with the real concentric oscillatory paths detectable in the video frames of BOLD resting state rs-fMRI activity. According to Mitra et al. (2015), each brain activity encompasses not just single, but also multiple lag threads. Our aim was to simulate the two threads shown in Figure 6 from Mitra et al. (2015). Both these two threads display four nodes, but the temporal order of their wave propagation is different.

The basic unit, i.e., the rectangular-shaped channel with two inputs and two outputs channels, can be expanded via nesting and cascading processes to build multi-bit digital comparators. We connected and combined several basic units to build the complex lag threads described in **Figures 3A and 3B**. **Figure 3A** illustrates the circuit designed for the description of thread 1, consisting of four (neuronal) units and ad hoc connections among them. The yellow arrows depict the direction of signal transmission. The signal input starts from the left side of the node 1 and enters the node 1 through the unidirectional transmission structure designed to prevent the signal from the opposite direction to output through the input channel. When the signal propagates to the rectangular-shaped channel, it splits in two wave fronts. After passing through half a rectangle in different directions, their wave fronts meet at the opposite side, enter the gap into the T-shaped structure and continue to node 2. Summarizing, the input enters node 1, crosses nodes 2 and 3 and the output exits node 4.

Figure 3B illustrates the circuit designed for thread 2, consisting of four neuronal units and the corresponding connections too. The red arrows depict the direction of signal transmission. This time, the input enters node 4, crosses nodes 3 and 1 and the output exits node 2. It is noteworthy that the connection between nodes 1 and 2 is the same in the two threads, so that signals always propagate from node 1 to 2. The sequence that crosses the nodes 1 and 2 is termed “lag thread motif”.

Mitra stated that the spontaneous activity of the brain is achieved through the superposition of multiple threads. Therefore, we produced a more intricate circuit encompassing multiple lag threads. **Figure 3C** illustrates two-threaded superposition (thread 1 and 2). The yellow and red arrows depict the direction of signal transmission in thread 1 and 2, respectively. Note that the two signals stand for simultaneous inputs for two different channels. Signal 1 from thread 1 and signal 2 from thread 2 simultaneously reach the output channels in node 2 and node 3, respectively. Therefore, signal 1 outputs node 4 after crossing node 3, while signal 2 outputs node 2 after crossing node 1. This is in touch with the observation that signal transmission is constrained in threads: for example, in the two threads

1 and 2 of **Figure 3C**, the node 1 is able to transmit signals just from left to right, while the node 4 is able to transmit signals both from left to right and right to left.

In case of a single thread, the node-like structure is a unit with a single input and a single output; in a two-threaded superposition, the node-like structure is a unit with two inputs and two outputs; in a three-threaded superposition, the node like structure is a unit with three inputs and three outputs, and so on. Increasing the number of threads, more complex structures are achieved that permit higher number of computations.

BZ-like circuits generate synthetic oscillations that tend to propagate, converge, merge/annihilate and so on, giving rise to travelling waves that closely resemble the real oscillations detectable in the chemical BZ. The next step was to incorporate our synthetic oscillations in a template resembling the brain shape and anatomical structure in transverse projection. Using our BZ-like circuits, we generated random concentric wave fronts and projected them to the brain template (**Figure 3D**). We randomly generated simultaneous waves arising from different starting points inside the brain template to investigate their intersections and interactions.

Results

We found that the patterns of signal transmission in simulated BZ-like travelling waves match the oscillatory patterns detectable in the spontaneous activity of the brain. The experimental data from real BOLD resting state rs-fMRI data agree well with our simulated wave fronts, showing a good superimposition. The neural wave fronts closely resemble the BZ-like concentric circles embedded in the brain template. Indeed, matching features between the simulated and real oscillations were found in 85% of the 54 examined frames and in 65% of all detectable oscillations, independent of brain location and time window.

Concerning interactions and superpositions between distinct oscillations, two different cases can be described both in real and simulated travelling waves:

1) a single wave gives rise to a wave front that proceeds through the cortical areas. 2) Two waves cancel one each other when they start to merge and overlap.

To provide an example of the case 1, the upper part of **Figure 4A** illustrates the signals of thread 3 from 0.4s to 1.1s, while the lower part of **Figure 4A** illustrates the corresponding artificial signals produced by BZ-like circuits. The two travelling waves, the real and the simulated one, display the same progression throughout the brain template. To provide an example of the case 2, see **Figure 4B**, which illustrates two waves that annihilate when intersecting.

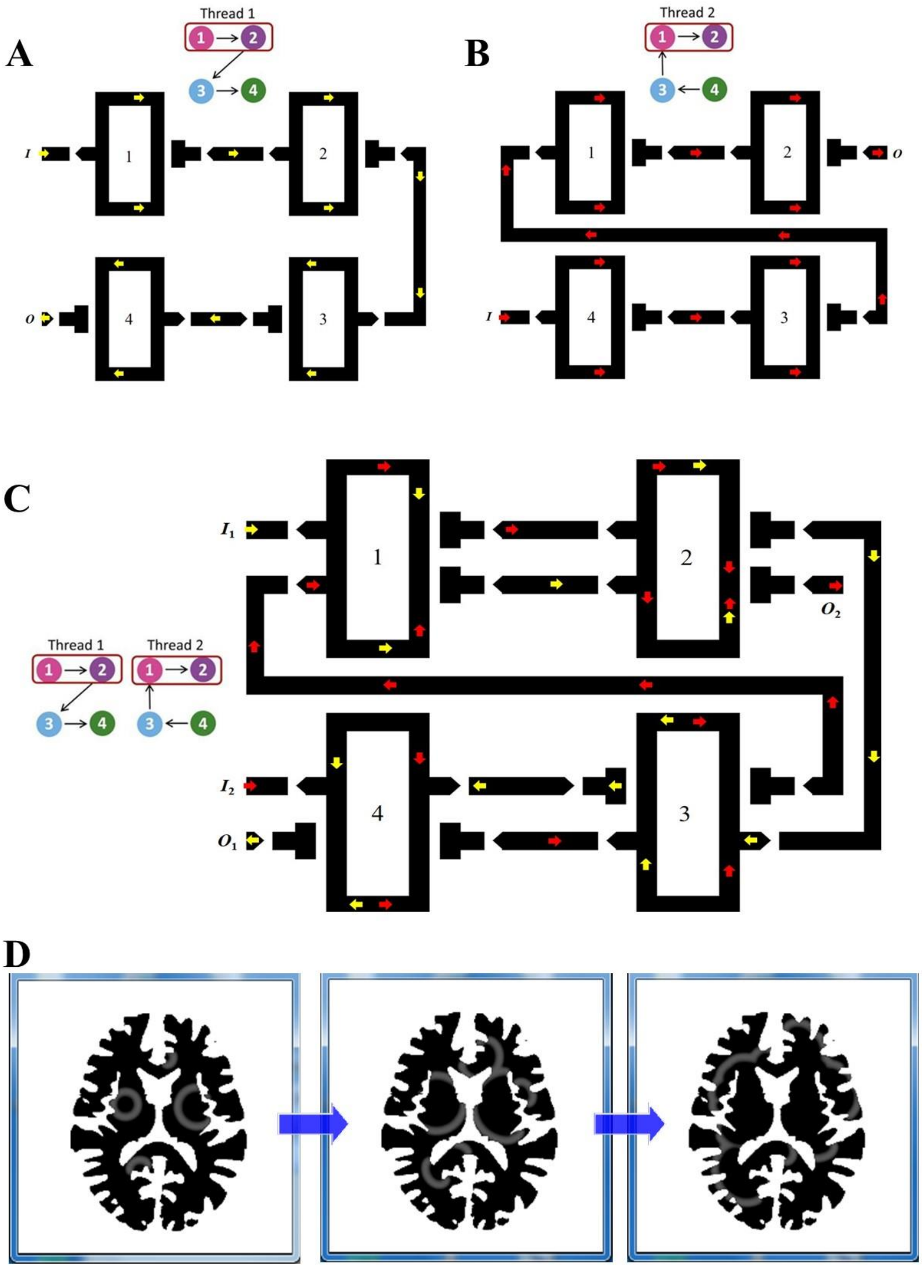

Figure 3. The lag threads detectable in the spontaneous activity of the brain can be described in terms of BZ-like circuits. **Figures 3A-B** illustrate simulations with four neuronal unities inspired by the lag threads described in the video frames of BOLD resting state rs-fMRI activity. The arrows depict the direction of signal transmission from the input to the output. The numbers 1,2,3,4 designate four rectangular structures, each one standing for a neuronal unit. **Figure 3A**. Simulation of signal crossing in thread 1. **Figure 3B**. Simulation of signal crossing in thread 2. **Figure 3C**. Simulation of two simultaneous signals crossing in threads 1 and 2. The yellow arrows show the signals of thread 1, the red arrows the signals of thread 2. **Figure 3D**. Simulation of the temporal evolution of three simulated BZ-like concentric patterns inside a brain-like template. Modified from Mitra et al.'s movies.

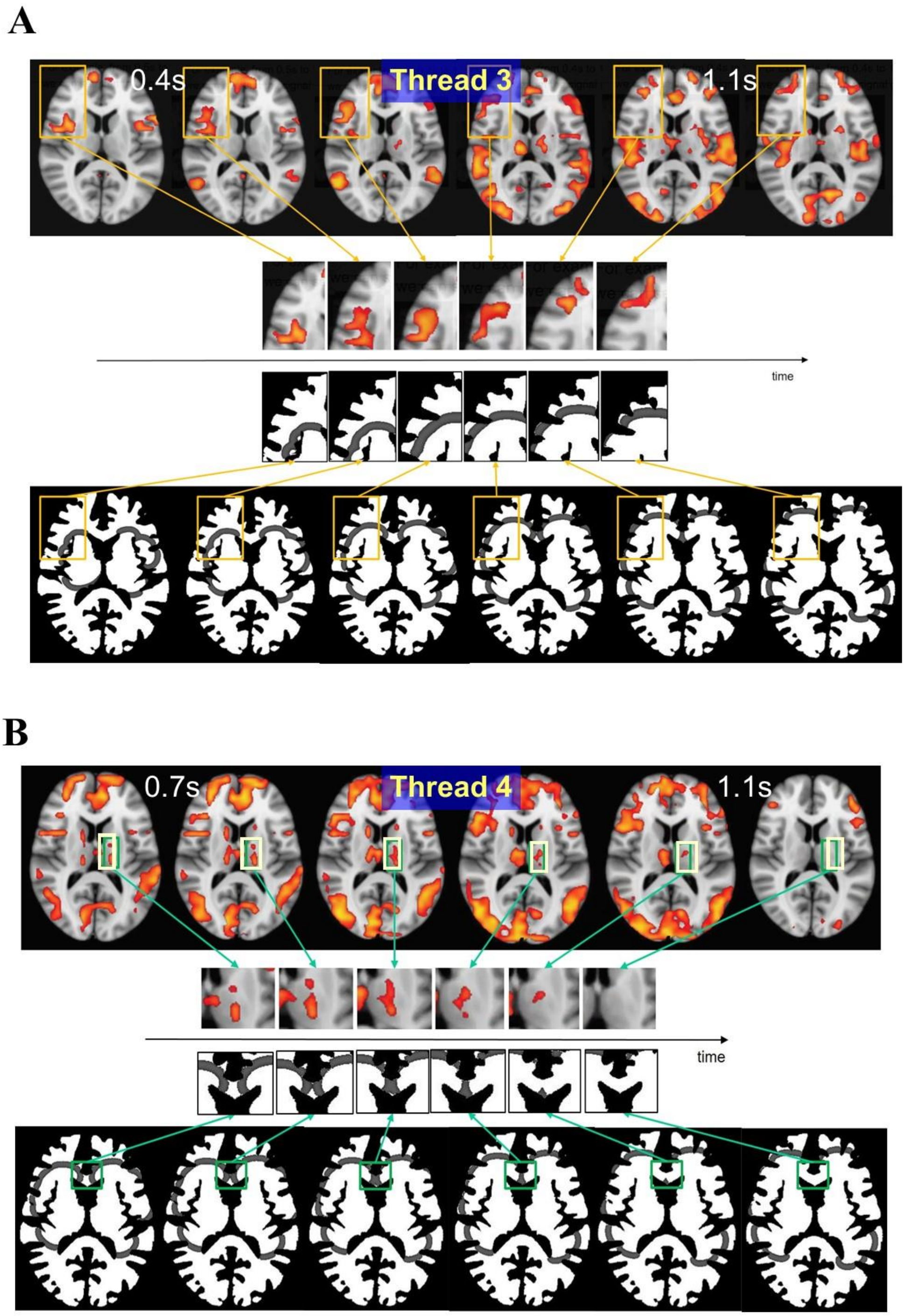

Figure 4. Comparison between wave fronts from real lag thread frames (**upper part**) and from simulations with the novel BZ-like circuit (**lower part**). The paths of the travelling waves can be easily detected and compared in both BZ simulations and real fMRI data. **Figure 4A** illustrates the progression of a real and a simulated single wave, while **Figure 4B** illustrates the annihilation of two simultaneous waves.

We found agreement between the waves produced by the spontaneous activity of the brain and the waves simulated by the novel network. This means that the diffusive paths detected in BOLD neuronal activity can be described in terms of BZ-like models and their master equations.

Conclusions

We found BZ-correlated dynamics in video frames of BOLD resting state rs-fMRI activity. The matching of theoretical BZ models and real patterns of neural activity allows us to achieve two goals. The first goal is the possibility to reproduce and standardize neural waves propagation in order to investigate different cognitive activities. To make use of video frames of BOLD resting state rs-fMRI activity as the domain of BZ, we began with two recently developed concepts:

a) each brain activity encompasses single or multiple lag threads (Mitra *et al.,* 2015);

b) chemical signal processors based on the BZ platform are available (Zhang *et al.,* 2012).

To mimic both single lag threads and the superposition of multiple lag threads, we designed relatively simple BZ-like structures where random oscillations propagate through a small number of nodes. We found that the oscillatory patterns of neuronal activity produced by simulations based on BZ fully overlap the oscillatory patterns detected in the brain during spontaneous activity. Therefore, the behavior of BZ travelling waves is very similar to the behavior of brain travelling waves: this suggests that logical devices based on the space-time interaction of travelling excitation oscillations is well-suited for experimental implementation in neuroscience (see also: Gomez-Molina *et al.,* 2017).

In this paper we assessed just coarse-grained macro-levels of observation and analysis: this led us to describe nodes at the level of cortical subareas equipped with inputs and outputs. Nevertheless, if we consider micro-levels of observation and analysis, nodes might also stand, e.g., for single neurons or micro-columnar circuits. A crucial question arises: is it feasible to generalize the description of nodes in BZ-like circuits, independent of the chosen coarse-graining? The answer is positive, because generalizations do not impair the broad description provided by threads. Indeed, BZ-like reactions provide a good sketch of both single threads and their subsequent superposition. In this paper we implemented just two-threads superpositions, while a more intricate superposition of multiple threads would require further exploration.

The matching of theoretical BZ models and real patterns of neural activity allows us also to achieve a second goal: to posit that the brain encompasses a recognizable diffusion pattern spreading throughout nervous structures. Cincotti et al. (2019) brought a new level of complexity to BZ by combining multiple wave sources in a so-called "threaded ring" configuration. The order in the fluids is never perfect, because contaminations and impurities may affect the values of order parameters. For example, a dust particle in the proper chemical medium may trigger spontaneous BZ waves consisting of concentric rings moving outward from the particle. In other cases, circular BZ wave fronts perturbed by obstacles (see the movie: https://www.youtube.com/watch?v=jRQAndvF4sM) transform into spirals and/or scroll rings, i.e., ring-shaped sources emitting circular waves which propagate both inwardly and outwardly from the source. It is noteworthy that impurities are always *local*, which means that they are small and affect just limited spaces of the medium. Peculiar local configurations termed *vortices* can be temporarily achieved when oscillations wind around a central point. Because vortices might also stand for topological defects in the crystalline order of a medium (Beekman *et al.,* 2017), this leads us into the field of superfluids and superconductors, where Kosterlitz-Thouless transitions (which describe ordered state at low temperature and completely disordered state at high temperature) are caused by topological defects in two-dimensional manifolds (Kosterlitz and Thouless, 1973). In neural terms, this means that each type of order (also the order of the brain activity) has its own type of topological defects, which presumably can undergo similar unbinding transitions caused by vortices. In touch with these claims, Don et al. (2020) used computational topology on triangulated rs-fMRI videoframes to detect vortex structures covering activated regions of the brain. During spontaneous activity of the brain, measure of persistence of vortex shapes was carried out in terms of Betti numbers that rise and fall over time (Don *et al.,* 2020).

To link up travelling neural oscillations to brain mechanisms of computations, virtues, defects and biological plausibility of our novel BZ-like network are here explained. We proposed a BZ-like network producing concentric waves from random multifocal sources located in a two-dimensional manifold. Although centered on binary operations like most neural networks, our network simulates the progression of concentric waves and their superposition through an operation of binary addition. In terms of biological counterparts, our model requires numerous nervous spots located in the central nervous system that spontaneously generate random oscillations propagating in concentric waves throughout the brain. When the oscillations produced by multifocal sources interact, they collide and merge, allowing us to achieve dynamics that are reproducible by BZ-like networks. Therefore, the main requirement for the biological plausibility of our model is the occurrence of spontaneous travelling waves in the brain. Indeed, the brain cortex is crossed by scattered spontaneous waves whose frequencies and speeds are consistent with slow conduction (Davis *et al.,* 2020). It is well established that spontaneous travelling waves in the brain are endogenously generated and are not triggered by explicit tasks (Northoff 2018). This "intrinsic" brain activity has been associated not just with resting-state or default-mode network (Tozzi et at. 2016), but also with disused circuits (Newbold *et al.,* 2020) and increased target-evoked neuronal responses/perceptual sensitivity (Davis *et al.,* 2020). Comparison between the oscillations produced by our model and the oscillations detected in fMRI traces suggests that the front waves of scattered spontaneous oscillations are circular and tend to propagate in concentric, expanding circles.

Our model permits the assessment of front waves' interactions: instead of investigating input features such as probability-weighted connections, activation functions, learning rates, thresholds and hidden layers, our BZ-like network focuses on the relationships between the various outputs, i.e., the concentric waves generated by point sources.

The process looks like natural evolution, by selecting the "best" concentric wave and eliminating the relatively poor ones, so that a single output from a very few spots far outshines the rest. Therefore, we suggest a winner-take-all approach, in touch with Pandemonium-like architectures (Selfridge 1957). Spontaneously generated concentric waves subtend a hierarchical, self-improving model able to perform non-trivial binary functions (Tozzi and Peters, 2018). A Pandemonium-based architecture have been already proposed to elucidate not just cellular homeostasis (Liu *et al.,* 2019), but also brain functions such as pattern recognition and mental interpretation of visual scenes (McDowell, 2010; Edelman, 2017). Here we propose to extend Pandemonium-based architectures also to the spontaneous activity of the brain, so that, in touch with "neural darwinism" (Rosenbaum, 2014), the concentric scattered waves become a selection system. The waves interaction described by our model might help explain a puzzling finding. It has been uncovered that neurons coordinate the strength of their excitatory and inhibitory inputs to establish and maintain a constant excitation/inhibition (E/I) ratio. E/I ratio is thought to be essential for circuit function and stability (Xue *et al.,* 2014; Sengupta 2013; Sengupta 2014; He and Cline, 2019) and is rather stable at different magnifications (He *et al.,* 2018). E/I ratio stability can be exposed as various coarse-grained levels of analysis, such as individual pyramidal neurons in vitro and in vivo (Haider *et al.,* 2006), ensemble of multiple cortical neurons (Xue *et al.,* 2014) neural avalanches (Lombardi et a., 2012), circuit assembly, intact and spontaneously active cerebral cortex. How a balance of excitatory to inhibitory inputs is established and subsequently maintained remains a matter of debate (He and Cline, 2019). To provide an example, Xue et al. (2014) suggested that optimal E/I ratio across neurons is maintained, despite fluctuating cortical activity levels, due to strengthening or weakening of synapses (Xue *et al.,* 2014). Our model suggests that the E/I ratio could be controlled (among other factors) by oscillations' collisions: when wave fronts interact, their merging gives rise to annihilation and intensification that provide a natural balance between excitatory and inhibitory inputs.

BZ-like circuits stand for an approach to neural networks different from the standard ones. The combination of the elementary modules, i.e., binary adder unit, allow the achievement of both series and parallel processing. Because of the intricate nature of excitable mediums and the high dependency on synchronized inputs both in chemical and in nervous settings, BZ-like networks require careful control of signals timing to achieve binary addition. Indeed, one of the main troubles with our model is time representation, since the human brain encompasses waves with different speeds, taking longer or shorter times to reach a target area. The same occurs inside the neural fibers of different diameter and diverse myelination. In our model, due to the scarce homogeneity of the connections between nodes, it takes different time for signals to pass through one node to another. To overcome the difficulty and achieve the required synchronous binary addition, a slight change in the channel length could be required. Since the signals are transmitted throughout the channels at the same speed, the lag time can be monitored and modified in two ways:

a) either by changing the channel length between nodes: 

b) or, since the speed of the signal slows down as it passes through the gap, by modifying the lag time with the addition of several channel gaps: 

When examining the very concept of lag thread, the term "lag" is a key innovation point, suggesting that it is worth to be incorporated in artificial nervous circuits. However, is it feasible to weight threads? The suggestion of Mitra et al. (2015) that different threads occupy different weights in brain activities is difficult to describe in the context of BZ-like approaches. For example, suppose that the weight of thread 1 is higher than the weight of thread 2. When simultaneous signals in thread 1 and 2 cross the structure, the signal 1 will obliterate the signal 2. This means that a functionally significant weight difference between distinct threads occurs. In turn, if the sole signal 2 crosses the circuit, it is left undisturbed. Further studies are required to design the proper structure able to treat differently signals coming from diverse threads.

Our network allows to appraise nonlinear dynamics in the plain terms of superimposing waves. In touch with our model, it is noteworthy that fluctuations of cortical activity are neither purely synchronous, nor spatially disorganized noise processes (Davis *et al.,* 2020). The matching of theoretical BZ models and real patterns of neural activity suggests that the occurrence of chaotic, non-linear activity during brain activity is correlated with peculiar topological and geometrical arrangements of the subtending neural circuits. BZ models for neural activity predict that the subtle balance between concentric oscillations produces nonlinear chaotic patterns of wave propagation. In touch with the BZ framework, the brain has been described as a complex, non-linear system operating at the edge of chaos, characterized by inter-dependent components, spontaneous self-organization and emergent properties (Tognoli and Kelso, 2013; Yan *et al.,* 2013; Xu and Wang, 2014; Kim and Lim 2015). Funnel-like locations in nervous phase spaces converge towards the shortest path as time progresses (Watanabe *et al.,* 2013; Tozzi *et al.,* 2016; Sengupta *et al.,* 2016; Wang *et al.,* 2017). Distinct nonlinear functional regimes have been described both in the central nervous system and in artificial neural networks (Deco and Jirsa, 2012; Touboul 2012; Afraimovich *et al.,* 2013). In agreement with brain dynamics, the solutions of BZ equations describe a wide range of nonlinear behaviors, including the formation of travelling waves and attractor-like phenomena, as well as self-organized patterns. BZ-like network models are relatively straightforward since they are equipped with simple logical devices such as Boolean gates, adders, counters, memory cells. Apart from the lengths of the channels and the proper arrangement of nodes and edges, no other adjustments, such as phase parameters or fine-tuning, is required by our network. This suggests that the emergence of nonlinear dynamics could be strictly correlated with the geometric and topological arrangement of the channels where wave propagation takes place. In the description of nonlinear neural issues, wave bifurcations might stand for phase transitions, while BZ dynamics might replace Hopfield networks and/or Hodgkin-Huxley/reaction diffusion models (Hopfield 1982; Yang and Wu, 2018). Therefore, the key to understand chaotic dynamics might lie in the constrained shapes of circuits, nodes and edges that provide the very arrangement of physical/biological networks. Paraphrasing the adage that the function creates the organ, our BZ-like model suggests that in a neural network the arrangement creates the function.

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