Comment

# A Computational Discussion on Brain Topodynamics
# Comment on “Topodynamics of Metastable Brains” by Arturo Tozzi et al.

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Tozzi *et al.* [1] present an exciting (algebraic) topological approach to formally underpin and realize the Operational Architectonics (OA) model [2][1] of brain-mind functioning. They call this approach *brain topodynamics* and it represents a novel intersection of OA and computational topology and proximity. Not only does this model advance our understanding of brain-mind functions, but it provides a solid theoretical framework to implement autonomous systems for mimicking human brain-mind activity. My interest in this work stems from a desire to create automated systems and applications that produce results similar to a human performing the same task. Along these lines, this paper comes at a time when society is dramatically benefiting from to two major developments – general purpose computing with graphics processing units (GPUs)s [3] and applications of deep artificial neural networks [4] – and it stems form the new areas of computational topology and proximity [5, 6] that ultimately may have equal effect, especially as the work reported in this paper is adopted and disseminated. Thus, the focus of this comment is to discuss the computational aspects of Tozzi *et al.*'s contribution in light of general purpose computing using GPUs, deep learning neural networks, and computational proximity; where the goal is the synthesis of human perception for autonomous systems that mimic human behaviour.

## 1. General Purpose Computing using GPUs

While Tozzi *et al.* identify that the presented approach could serve to inspire new computing systems with nodes built into high dimensions [p. 29], it is the case that the mappings, projections, and intersections inherent to the presented approach are ideally suited to current heterogeneous computing environments and hardware. Briefly, the traditional programming model of writing code to be executed exclusively on a central processing unit (CPU) has now given way to heterogeneous computing, where inherently serial portions of a problem run on the CPU and large data intensive, parallel portions are offloaded to the GPU, resulting in significant increases in performance [7]. In regards to the OA topodynamical framework, the heterogeneous computing model, and, specifically, GPUs have evolved many features that would allow aspects of the presented model to be realized in scientific computing applications. First and foremost, GPUs offer thousands of processors (within a single GPU) that can execute hundreds of thousands of active threads. Moreover, they offer simulated unified (*i.e.* shared) memory between the CPU and GPU; dynamic parallelism that allows the parallel threads to spawn new parallel processes (called kernels); and they provide task parallelism, which means multiple parallel tasks, again each consisting of very large numbers of threads, can be concurrently executing within a single application.

The result is that the following highlights from Tozzi *et al.*'s paper can be realized within a heterogeneous computing application. The paper begins [p. 1] with the notion that the brain displays a vast amount of interconnected topological mappings, which is a necessary condition for GPU applications as they require significant parallelism to offset the overhead in sending computations to the GPU and to mask long latency operations. Next, Tozzi *et al.* emphasize that neuronal assembly operations can be modelled by mappings and projections [pp. 7 & 19] that are both parallel and serial in nature. This approach to solving problems is also the same paradigm employed in heterogeneous computing systems. Further, the work of mapping trajectories from lower to higher dimensions and then looking for descriptive matches (*i.e.* intersections, likely tolerance based [8], between the higher dimensional antipodal points) is parallel in nature and will require significant resources if the number of neuronal assemblies is quite high. Again, this problem is a natural fit for heterogeneous computing systems and could be realized with existing (off-the-shelf) hardware. Additionally, dynamic parallelism is a mechanism that can be used to implement

[1] See their paper for full list of references for the OA model.

the dynamic and metastable components of the proposed approach, and task parallelism (with synchronization) could be employed when considering the work performed by isolated neuronal assemblies that eventually need to coordinate [p. 3].

Although these observations are promising, it is the case that brain topodyanmics model the complex relationships of *signals* generated by the human brain during brain-mind functioning, whereas the above comments lack any discussion of artificial system signals. Therefore, brain topodynamics cannot be implemented in isolation and requires a complementary system to generate signals, such as the outputs of human primary sensory areas [9], from external stimuli. One solution readily available is to extend the current state-of-the-art of artificial deep learning neural networks, which both generate large number of feature vectors (*i.e.* signals) during training & classification and, as will be discussed next, do not characterize human perception [10, 11].

## 2. Deep Artificial Neural Networks

In 2012, Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) – by a significant margin – using a deep learning convolutional neural network driven by GPUs [12]. Since then, deep neural networks have been successfully applied in many interesting applications to produce impressive results in many fields and applications (such as self-driving vehicles and real-time language translation). Nevertheless, they still suffer from several problems. In particular, these networks, fundamentally, classify feature vectors – obtained from objects within the context of some practical application such as digital image classification – into a number of finite categories or classes used in machine learning-based models. However, when developing systems to mimic human behaviour, there is a need for quantifying the similarity of sets and families of sets, composed of objects from both within and between given classes used in machine learning-based models. In other words, human behaviour is much richer than simply the ability to classify objects. We have a powerfully inherent ability to make judgements on the similarity of groups of objects, which we perform seamlessly and unconsciously many times a day. Thus, there is a strong need for theoretical frameworks, such as brain topodynamics, that can provide a mechanism for augmenting current deep neural network methods to account for the breadth of human perceptual capabilities. Similar sentiments have also been reported in recent work that indicates deep neural networks fail to simulate human perception of objects [10, 11]. The result is the emergence of an interesting new line of research based on the application of the work by Tozzi *et al.* to deep neural networks and machine learning. Examples include creating caricatures of operational modules (in the same manner as artificial neurons) for defining new artificial network architectures, investigating entropy variability in artificial neural networks [p. 18], developing an analogous application of the Borsuk-Ulam theorem, and determining if similar relationships between semantics and syntax can be developed for artificial neural networks [p. 19].

## 3. Computational Topology and Proximity

This comment ends with a conjecture regarding the future of descriptive and computational topology and proximity. The authors use the description "far flung field of algebraic topology" to introduce their work. In some sense, this is an adept description of topology, especially computational topology. Although, as has been shown in the paper by Tozzi *et al.*, the techniques discussed in [5, 6] can be used to develop very powerful theoretical frameworks to model both real-life processes and guide the design of artificial systems. Further, until recently, carrying out the multitude of operations (*e.g.* unions and intersections) described by topological approaches was too computationally complex and rigorous mathematical frameworks that captured features and attributes of objects in real-world systems were lacking. It was the introduction of descriptively near sets and descriptive proximity [13, 5] that have provided theoretical blueprints for practical computing applications. These ideas are ancillary to the central contribution of [1], but are present when the authors refer to descriptively similar points and descriptive closeness. Thus, with the advent of descriptive approaches to topology and proximity, the theoretical frameworks now exist to systematically create automated systems that depend on the assessment and quantification of the nearness or apartness of points and sets, sets, and families of sets. Moreover, the introduction of general purpose computing using graphics processors has democratized high-performance computing, and has provided personal computers the ability to perform trillions of floating point operations per second. This confluence of descriptive set theory and computing hardware – capable of realizing the 1000s of topological operations – means that computational approaches to topology and proximity are reaching a tipping point in terms of practical applications. Consequently, I conjecture that the paper by Tozzi *et al.* will spur others to apply descriptive and computational approaches to topology and proximity in their work to realize similar advances in their respective fields.

## References


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