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Visual Experiences and their Neural Substrate as Parts of a Dynamic Whole

Introduction

This paper deals with a long-standing and central problem in vision. It is well known that the visual system actively constructs visual experiences, but there is no scientific account that tells us how to get from properties of perception to those of the neural substrate and back. In fact, there is little agreement about which perceptual and neural properties might form the basis for a theory.

There are excellent reasons for turning to Gestalt Psychology for help with this difficult problem. Beginning with Max Wertheimer's seminal publication on phi motion (Wertheimer, 1912) and continuing over the ensuing century, evidence that gestalts play a foundational role in vision has accumulated. The existence of pure visual motion as possessing singular phenomenal properties that are not derivative on simpler sensations directly raises the possibility that the motion-gestalt is that which emerges from interactions among the neurons of the visual system. It is likely that other visual gestalts also emerge from neural interactions (e.g., Lehar, 2003a,b), and that the result is the familiar organization of the visual field (Todorović, 2011). Evidence demonstrating the "gestalt-first" nature of vision (Chen, 2005) is of particular importance, because objective properties of gestalts that serve as visual primitives might serve to anchor phenomenal vision to neural activities.

The purpose of this paper is to demonstrate that an approach that assigns equal theoretical importance to properties of the visual gestalt and to those of its neural substrate makes possible the construction of a testable model that specifies the organization of the gestalt in terms of relations among neural information states. I will begin by briefly discussing results of research conducted by Lin Chen and his colleagues which highlight properties of gestalts that serve as visual primitives. Next, I will describe some results of my neural network research which suggest that the information that a neural network has about its own states may serve as a bridge to the visual gestalt. I will then briefly describe a new model that relates visual gestalts and neural network information states, and I will end with some ideas for testing and extending the model.

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Gestalts that Serve as Visual Primitives

Vision research is dominated by work that is based on the assumptions that visual processing proceeds from local to global, from computationally simple to complex, and from phenomenal part to whole (see discussion by Chen, 2005). Such assumptions are routinely given more weight than other assumptions that might follow from what is known about perceptual organization. However, the commonly-held assumptions that vision is fundamentally a part-to-whole, computationally simple-to-complex, and local-to-global process are challenged by a series of studies carried out by Lin Chen and his colleagues.

Aspects of visual gestalts that are invariant under certain types of transformations form the keystone of Chen's work. According to Chen's (2005) theory of topological structure and functional hierarchy, visual perception is fundamentally global in nature, and this is described by the primary role of topological invariants in vision. Topological transformations change the locations, shapes, and sizes of visual images, but do not change the connectivity, the number of holes, or the inside-outside relationship of an image (see Mendelson, 1990 for an exceptionally clear introduction to topology). Therefore, these latter three properties are invariant under topological transformations. The theory also holds that global topological perception is temporally prior to the perception of other featural properties that represent geometrically less stable, and therefore more local aspects of a visual image, such as its shape and size. Using a variety of methods, Chen and his colleagues have demonstrated that gestalts that are invariant under topological transformations are more perceptually salient and are extracted more rapidly by the visual system than are other types of visual features (Chen, 1982, 1985, 1990; Chen & Zhou, 1997; Todd, Chen, & Norman, 1998; Zhou, Zhang, & Chen, 2008). According to Chen (2005), such gestalts serve as visual primitives.

Several types of evidence provide converging support for Chen's theory. For example, illusory conjunctions of certain kinds of visual features occur when demands are placed on attention (e.g., Treisman and Gelade, 1980). If topological properties are visual primitives, then illusory conjunctions of properties such as holes should occur. Using a very conservative estimation procedure, Chen and Zhou (1997) found that illusory conjunctions of topological properties occurred on 17.6% of trials.

There is a great deal of additional evidence for Chen's contention that topological invariants serve as visual primitives. Both two- (Chen, 1982, 1990) and three-dimensional stimuli (Todd, Chen, & Norman, 1998) that differ in topological properties are more discriminable and are more rapidly identified than stimuli that differ only in non-topological properties. Furthermore, subjects experience apparent motion between stimuli that are topologically equivalent even when the objects differ in shape (Chen, 1985), and fMRI shows corresponding activity in the anterior temporal cortex (Zhou, Zhang, & Chen, 2008).

This work is highly relevant to the task of bridging the visual gestalt and its neural underpinnings. Topologically-invariant structures may define what it means for something to be perceived as an object, and their objectively-defined properties can be used to anchor visual phenomena to the neural substrate. These structures are holistic, and they are properly termed gestalts. What properties of neural activity are related to such gestalts?

Information in Richly-Interconnected Neural Networks

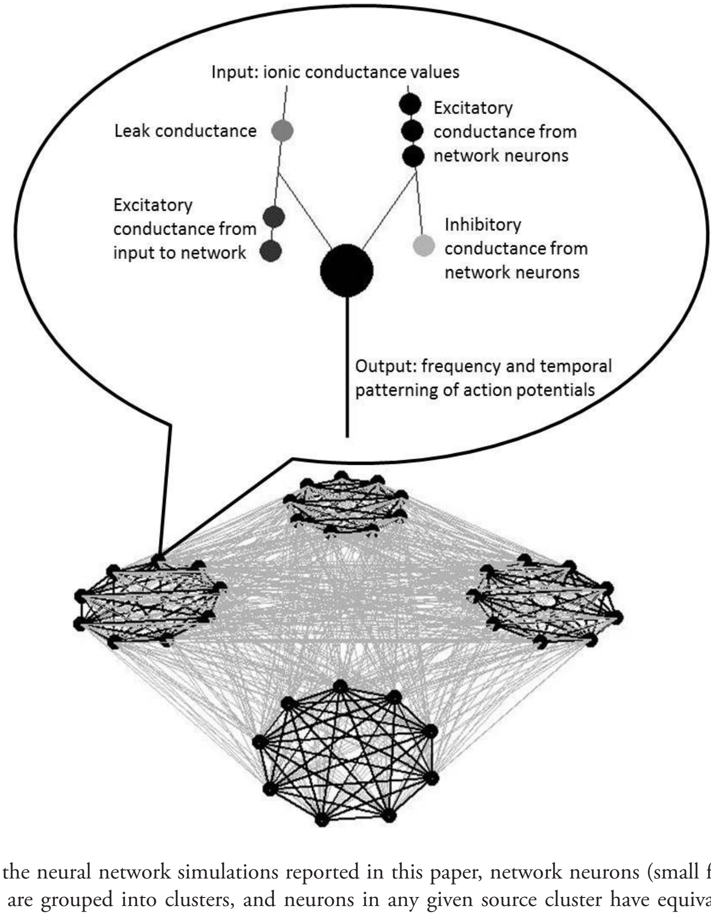

Fig. 1. In the neural network simulations reported in this paper, network neurons (small filled circles at bottom) are grouped into clusters, and neurons in any given source cluster have equivalent effects on neurons in any given target cluster. There are synapses between all pairs of neurons in the network, shown as heavy black lines between neurons comprising each of four clusters, and as lighter gray lines between neurons in different clusters. Inputs to the network are not shown on this figure. One model neuron is shown in an expanded view on the top part of the figure, where the action potential outputs carried by the axon that form the typical focus of neural network simulations are contrasted with inputs to dendrites. The focus of research using these simulations is on simulated ionic conductance values produced within network neurons by network neurons, because it is these conductance values that constitute the information that each network neuron has about the state of its network.

I have argued that it may be fruitful to think of vision in terms of how a network of neurons represents its own activity – to focus on *inputs* to neurons (Pavloski, 2006, 2008, 2010, 2011; see Figure 1). The most common result of input to a neuron is a change in the conductivity of that neuron's membrane for a specific type of ion. A conductance value at a synapse constitutes a reduction of uncertainty about the state of the network of which the neuron is a part, and therefore provides information that the neuron has about the state of its network. At a larger scale (e.g., the scale of a small neural network), a pattern of conductance values might be organized into a form along dimensions that we recognize as describing a visual gestalt. Restated from a visual perspective, a gestalt might be a holistic and complex information state that organizes a set of individual conductance values at the scale of a neural network.

Motivated by this possibility, my research for the past 6-7 years has focused on analyzing the results of computer simulations in order to determine how patterns of conductance values are organized by the activities of richly-interconnected neural networks (Pavloski, 2006, 2008, 2010, 2011). In these simulations, network neurons are grouped into clusters (of nine excitatory neurons and one inhibitory neuron) in order to promote stability. Each neuron receives inputs from all network clusters, including from its own cluster. All neurons in a source cluster have equivalent effects on all neurons in a given target cluster, up to random variation.

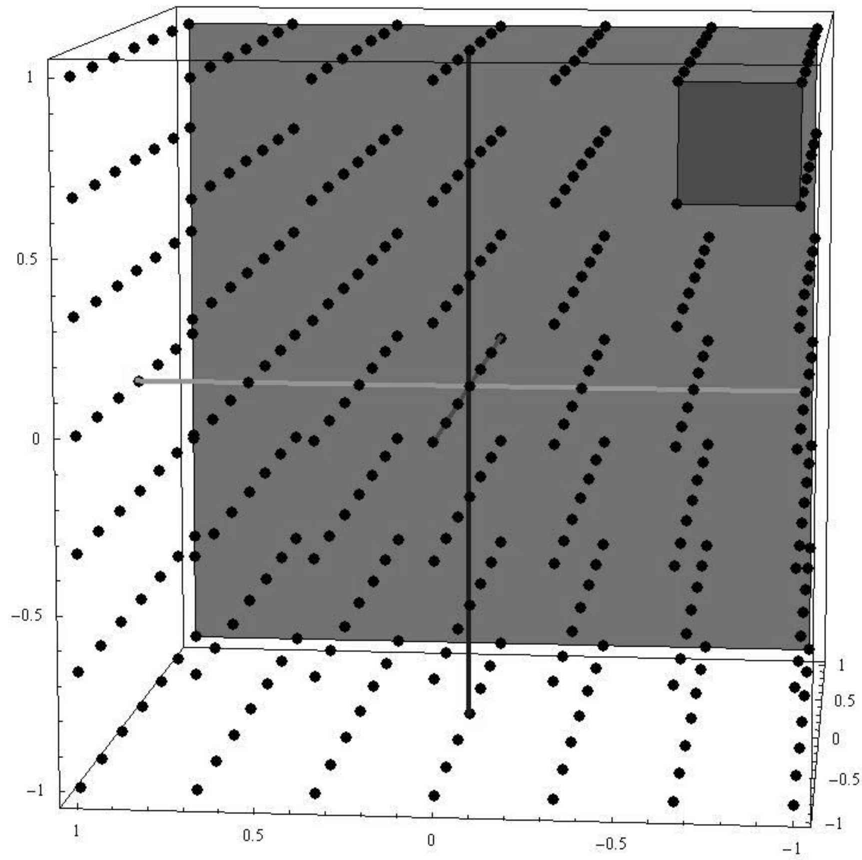

Fig. 2. The clusters of simulated neurons were assigned fictional positions as shown by the black disks in this illustration, and the strength of each synapse from a source cluster to a target cluster varied inversely with the fictional distance between the pair. The results of computer simulations described in the text were obtained by applying inputs above resting baseline levels (i.e., random firing) to four clusters on the first of the sheets of clusters, and to all clusters on the seventh sheet.

In these simulations, the strengths of synapses are based on a network-wide rule designed to promote the emergence of patterns of conductance values with a three-dimensional, visual space–like structure. In the example shown in Figure 2, 343 clusters were assigned fictional positions on seven square sheets organized into a cubic shape, and synaptic weights from source to target decreased with the fictional distance from source to target. For each simulation, input was provided in some pattern to the neurons that composed the 343 clusters of this network and the states of all neurons in the network were updated until a stable pattern of ionic conductance values was achieved. In the example illustrated in Figure 2, excitatory inputs were applied for a total of 16 updates to neurons in four clusters on the first sheet and to neurons in all 49 clusters on the seventh sheet.

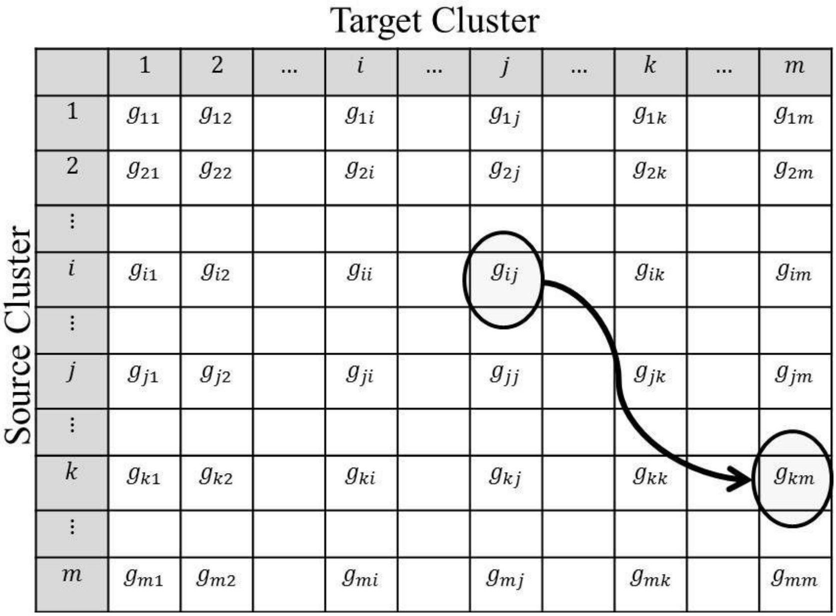

Fig. 3. The information that a neural network has about its own state is collected in a matrix of simulated ionic conductance values g_{ij}, where the first index i represents the cluster that is the source of input to the target cluster j. The information that a network with m clusters has about its own state is therefore represented by an m x m matrix G. For the example network described in the text, m=343. If the individual conductance values were not related, all 343 dimensions would be required to represent this information. However, singular value decomposition (SVD) of such matrices indicates that only 4 dimensions account for over 99% of the variance in conductance values. Three of these dimensions describe the fictional *positions* assigned to clusters, and the remaining dimension describes the information that each cluster receives about its own state (i.e., diagonal elements g_{ii}), which is referred to as *contrast* in the text. Therefore, to change the value g_{ij} to the value g_{km}, the *contrast* of cluster i must be transformed to the contrast of cluster k, and the *distance* between clusters i and j must be transformed to the *distance* between clusters k and m.

At any point in time, the information that the network has about its own state can be collected in a matrix of conductance values, as depicted in Figure 3. For example, g_{12} is the total conductance in cluster 2 neurons due to neurons in cluster 1. Singular value decomposition of the matrix (Deerwester et al., 1990; Kalman, 1996; Landauer et al., 1998) shows that the input conductance values in each cluster self-organize along only four dimensions – a three-dimensional position and a dimension showing the information that each cluster receives from its own neurons. The magnitudes of the 55 largest singular values (out of 343) are plotted at the top of Figure 4. To be consistent with calling the dimensions corresponding to three of these values *position*, the remaining dimension that corresponds to the singular value with the largest magnitude will be referred to as *contrast*.

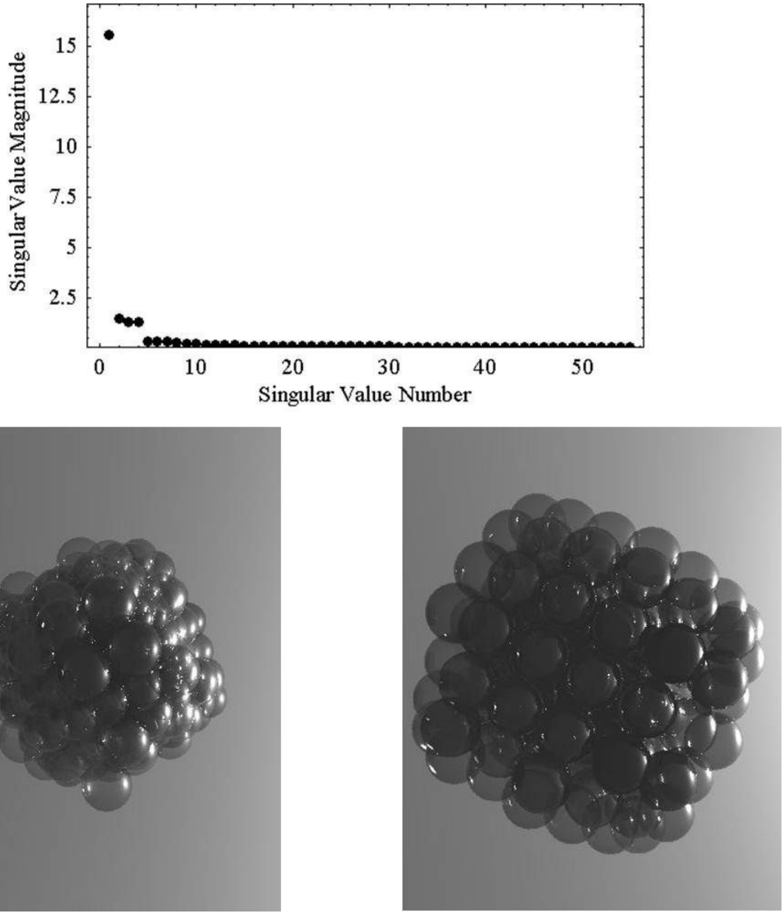

Fig. 4. The 55 largest singular values resulting from SVD of a matrix G are illustrated in the graph shown at the top of this figure. The entries were obtained from a simulation of a network with 343 clusters of model neurons by applying input from outside the network as described in Figure 2 for a total of 16 updates of all network neurons, and summing the individual conductance values from simulations 9-16 inclusive (in order to reveal the stability of the pattern of ionic conductance values). The resulting values of the 343 clusters on the *position* and *contrast* dimensions are shown from a view facing the first sheet of clusters on the left bottom panel and from a view facing the seventh sheet of clusters on the right bottom panel. The software package *Radiance* (Larson & Shakespeare, 2004) was used to render images of glass spheres representing the clusters. As the value of a cluster on the *contrast* dimension increases, the light transmittivity of the simulated glass is decreased.

Plotting the values of the 343 clusters on these four dimensions, as in the bottom part of Figure 4, shows that the network represents its own state in a way that reflects closely the assignment of fictional *positions* to clusters. The *position* values of the 343 clusters in this simulation nearly form a cubic shape, and the pattern of input determines the *contrast* values of clusters. Very similar results have been obtained for networks of different sizes and with different patterns of input. In every case, networks composed of hundreds of clusters and thousands of neurons respond to input by self-organizing the information that they receive from the network along these same four dimensions.

These results show that a stable pattern of relationships among conductance values is produced along these dimensions of *contrast* and *position* by the network in response to input. As depicted in Figure 3, these relationships can be described in terms of transformations: to change the value g_{ij} into g_{km}, we must transform the *contrast* of cluster *i* into the *contrast* of cluster *k*, and transform the *distance* from *i* to *j* into the *distance* from *k* to *m*. Thinking about the relationships among the conductance values in terms of phenomenal attributes of a visual gestalt such as *position* and *contrast* suggests a starting point for constructing a model that includes both the conductance values and their transformations, and that demonstrates how they are related to gestalts that are invariant under certain transformations.

However, these results are also far from telling us how neural activities and phenomenal visual organization might be related. How does one model connections across the epistemological gap that separates neural activity and a phenomenal gestalt? The answer cannot be found in neural dynamics as such. As Chalmers (1996) has said, from dynamics one gets only more dynamics. Appeals to "emergence" do not by themselves give us the means of relating the neural and the phenomenal, either.

A Bidirectional Strategy: Working "Bottom-Down" from Gestalts and "Top-Up" from Neural Network Information States

I propose that we treat a visual gestalt and the pattern of neural information states both as given, as they indeed are. A great deal of work in the area of complexity over the past 40 years has shown that more complex, larger-scale phenomena and their less complex, smaller-scale constituents must be placed on an equal footing if we are to understand how they are related. Physicists have done much to clarify the limitations of reductive science: while it may be possible to find smaller scale and simpler systems that provide the foundation for larger scale and more complex systems, this does not imply an ability to start with what is known about the simpler, smaller scale systems and to reconstruct those at a more complex, larger scale (Anderson, 1972; Laughlin, 2005).

Applying this general result to the specific case of visual gestalts implies that a reductionist account of phenomenal perception in terms of neural activities will not suffice as a strategy for understanding the links between visual phenomena and their neural substrate. I suggest that achieving an understanding requires working from those phenomenal gestalts that serve as visual primitives "down" to the neural activities that provide their structure, and from patterns of neural activity that are organized along phenomenal dimensions "up" to the gestalts that they structure. This approach could be used to help deal with difficult conceptual issues that are faced both by the currently popular part-to-whole approach (Chen, 2005; Lehar, 2003a,b) and by the Gestalt approach (Wagemans, Feldman, Gepshtein, Kimchi, Pomerantz, van der Helm, & van Leeuwen, 2012).

Implementing the bidirectional strategy requires finding a conceptual tool that is flexible enough to include both neural information states and their transformations, and that relates them to phenomenal gestalts. Category Theory (Adámek et al. 2009; Awodey 2010; Lawvere & Schanuel, 2009), a branch of mathematical logic, is very well suited for the construction and analysis of such a model.

An Algebra of Transformations of Neural Network Information States

A category consists of formal objects, depicted as the nodes of a graph, and of arrows that point from a source object toward a target object as illustrated in Figure 5. Arrows are most important in categories, because a category is, essentially, an *algebra of arrows*. The arrows in any category compose according to some rule that generalizes the idea of multiplication. Identity arrows (such as 1_A, 1_B, 1_C, 1_D in Figure 5) generalize the role that the number 1 plays in multiplication. And, composition is associative in a way that generalizes the associativity of multiplication of numbers.

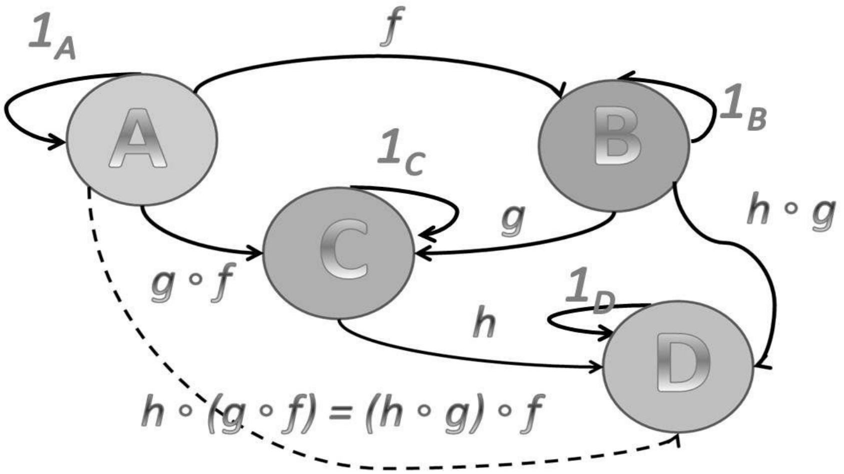

Fig. 5. The essential characteristics of a category are illustrated. Four categorical objects A, B, C, and D are shown with identity arrows 1_A,1_B,1_C and 1_D, and with arrows between each pair of objects. Each category includes a rule for composing arrows, and the requirement of associativity of composition is illustrated. The identity arrows play a role analogous to the unit in multiplication, as described in the text.

More specifically, there must be a law of composition that holds for the category (see Figure 5): If f is an arrow from object A to object B, and if g is an arrow from object B to object C, then these arrows must compose to yield the composite arrow g *following* f $(g \circ f)$ from A to C. Also, each object must have an identity arrow that acts as a kind of unit in the sense that the composite $f \circ 1_A = f = 1_B \circ f$. Thus the identity plays a role like that of the unit digit in multiplication. The law of composition of arrows for any category must also be associative. If there is an arrow h from object $C \rightarrow D$, then we can form the composite $h \circ (g \circ f)$. We can also form the composite $(h \circ g) \circ f$. Associativity means that these two composites are equal: $(h \circ g) \circ f = h \circ (g \circ f)$.

These simple requirements describe the sense in which a category is "an algebra of arrows." It is surprising that they allow a single category to represent a large and complex system. When applied to mathematics, a category has been referred to as a "mathematical universe" (Lawvere & Schanuel, 2009). A single large category can represent an entire area of mathematics (such as the category of all sets and functions on sets, and the category of all vector spaces and linear maps). Categories have also been used to model systems of many kinds. The theoretical biologist Rosen (1958a,b) appears to have been the first to model biological systems using category theory. Another notable application is that of Oksala (1979), who utilized categorical concepts in the area of formalized architectures.

Much more recently, Ehresmann and Vanbremeersch (2007) have significantly extended the use of category theory in their models of natural and social systems. In these models, objects correspond to components of various complexities of a system at a given time, and arrows depict relations between the objects. Some possible types of relations are spatial, causal, energetic, and those representing constraints. Their goal is to capture the *configuration* of the system at or around a given time as a category.

An essential component of the approach taken by Ehresmann and Vanbremeersch (2007) is the categorical construction of a *colimit*. The colimit provides a formal definition of a gestalt (Kainen, 1992): a colimit is a complex object, and its organization is given by a pattern of simpler objects and arrows. As a single object a colimit is functionally equivalent to that pattern within the category (Ehresmann and Vanbremeersch, 2007).

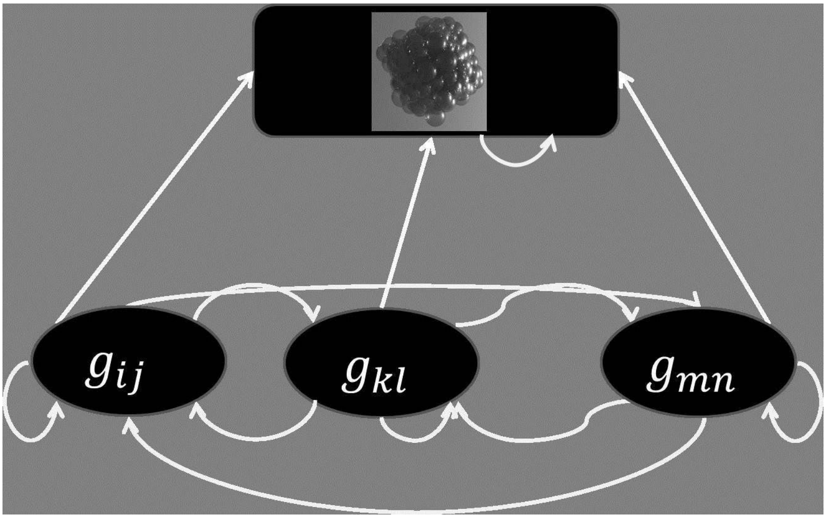

Fig. 6. A very small algebra of transformations of neural network information states is depicted. In this category, each object is a conductance value – information state and each arrow is a transformation of phenomenal properties of the gestalt that would change the source object conductance value into the target object conductance value (e.g., see Figure 3 and its description in the text). Each arrow from a conductance value to the gestalt-colimit spatial structure transforms a cluster *contrast* to the set of all *contrasts*, and transforms the *distance* between a pair of clusters to the set of all such *distances*. The identity arrow on the gestalt-colimit spatial structure consists of all transformations of the spatial structure that leave *contrasts* and *distances* unchanged.

In the model proposed here, the spatial structure of *contrasts* revealed by singular value decomposition of the matrix of conductance value information states is identified as a colimit (see Figure 6 for details). This gestalt consists of the information that the entire network has about its own state. Its organization is specified by a pattern of conductance values and transformations of those values. Each arrow in this pattern consists of the transformations of *contrast* and *distance* that change a source object conductance value into a target object conductance value. For example, the arrow from g_{ij} to g_{kl} transforms the *contrast* of cluster i to the contrast of cluster k and transforms the *distance* from cluster i to cluster j into the *distance* between clusters k and l. The identity arrow on each object makes no change in *contrast* or *distance*. The algebra of arrows in this category is based on straightforward rules for composing these transformations: when an arrow from g_{ij} to g_{kl} is followed by an arrow from g_{kl} to g_{mn}, the composite arrow transforms the *contrast* of the source cluster from the object at the tail of the first arrow (cluster i) and the *distance* from the source cluster to target cluster of that object (the *distance* from cluster i to cluster j) into the *contrast* of the source cluster from the object at the tip of the second arrow (cluster m) and the *distance* from the source cluster to target cluster of that object (the *distance* from cluster m to cluster n).

Each arrow from a conductance value to the spatial structure colimit, or gestalt, shown in Figure 6 transforms the *contrast* of a single cluster into the set of all *contrast* values, and transforms the *distance* between a pair of clusters into the set of all *distances* between clusters. The identity arrow on the spatial structure colimit is especially interesting. A transformation that does nothing to this spatial structure would serve as an identity. However, non-zero translations and rotations and a variety of mirror reflections of the entire spatial structure also leave the *contrasts* of the clusters and the *distances* between them intact. The colimit-gestalt is invariant under these transformations.

The category model provides a theory of how a visual gestalt is related to its neural substrate. Conductance values in network neurons that are due to input from network neurons comprise all of the information that the network has regarding its own state. According to the model, the organization of the gestalt corresponds to an algebra of transformations among the conductance value – information states. Therefore, the visual gestalt is a complex information state at the scale of the network-as-a-whole, and the arrows between conductance values represent transformations of phenomenal properties of the gestalt that would change the conductance at the tail of the arrow to the conductance at its head. The identity arrow on the visual gestalt consists of all transformations that do not change the gestalt. Therefore, the gestalt is defined by properties that are invariant under those transformations. It is this property of colimit identity arrows that the model puts forward as a bridge to visual gestalts that have been shown to be invariant under certain types of transformations.

Discussion: Extending and Testing the Category Model

A testable model should accommodate a gestalt-colimit that is invariant under topological transformations. This would allow a direct connection to be made between results of neural network simulations and the body of work conducted by Chen and his colleagues demonstrating that topological invariants are visual primitives (Chen, 2005). With such a model, it might be possible to make novel predictions regarding relationships among phenomenal gestalts in terms of transformations. Such predictions would provide an immediate test of the category model.

It is also possible to use results provided by Ehresmann and Vanbremeersch (2007) to extend the model by dealing specifically with the emergence of the large-scale information state that constitutes the visual gestalt. This can be done by using the categorical concept of *complexification* developed by those authors. This extension of the present model, and other extensions that include arrows (transformations) between gestalts, are beyond the scope of the present paper.

Also, it is not too early to begin thinking about how electrophysiological and brain scan data might be used in order to test the category theory model's view of a visual gestalt as a large-scale information state having an organization provided by conductance values and their transformations. This requires having one or more neural correlates of a category of neural network information states and their transformations. To achieve this, large-scale brain simulations of neural networks that accurately simulate the visual system are needed (de Garis, Shuo, Goertzel, & Ruiting, 2010). A report published this year by members of the Partnership for Advanced Computing in Europe suggests that it may soon be possible to visualize output from large-scale brain simulations in a way that is similar to what can be obtained from electrophysiological recordings and noninvasive brain scans (Benjaminsson et al., 2012). This capability would enable us to perform large-scale simulations of neural networks and to visualize neural signatures of the processes that occur as categories come into existence. Such a signature could then be used as a dependent measure in human brain scans.

Summary

A century of Gestalt research reveals that the gestalt is a foundational element in vision, and that topologically-invariant gestalts are visual primitives. Over the same period of time, it has been shown that phenomenal vision depends on specific interactions within and among neural networks. However, we have not found a way to deal with the epistemological gap that stands between perceptual organization and the neural interactions on which it depends. I previously proposed that progress on this issue would be facilitated by a formal model, the abstract elements of which encompass and bridge the phenomenal and the neural (Pavloski, 2011). By using category theory to model the results of computer simulations, this paper demonstrates how the pattern of information that a neural network has about its own state can be bound into a gestalt. A goal for future research is the construction of similar models in which gestalts are invariant under topological transformations. Such models would be consistent with research demonstrating that the global nature of perceptual organization can be described in terms of topological invariants. Tests of these models using predicted relationships among phenomenal gestalts in terms of transformations, and using neural signatures of categories of neural network information states and their transformations, are suggested.
Keywords: Category theory, conscious experience, emergence, visual gestalt, recurrent neural networks.

Zusammenfassung

Ein Jahrhundert Gestaltforschung zeigt, dass die Gestalt ein grundlegendes Element des Sehens ist, und dass topologisch-invariante Gestalten visuelle Primitiva sind. Im gleichen Zeitraum wurde gezeigt, dass phänomenales Sehen von spezifischen Wechselwirkungen innerhalb und zwischen den neuronalen Netzen abhängt. Allerdings haben wir keinen Weg gefunden, um mit der erkenntnistheoretischen Diskrepanz zwischen der Wahrnehmungsorganisation und den neuronalen Prozessen, von denen sie abhängt, umzugehen. Ich habe schon früher vorgeschlagen (Pavloski, 2011), dass Fortschritte auf diesem Gebiet durch ein formales Modell abstrakter Kategorien, das eine Brücke vom Phänomenal-en zum Neuronalen schlägt, erzielt werden kann. Durch die Verwendung der Kategorientheorie, mit deren Hilfe die Ergebnisse der Computersimulation modelliert werden, zeigt dieser Artikel, wie das Muster der Informationen, über die ein neuronales Netzwerk über seinen eigenen Zustand verfügt, Gestaltcharakter hat. Ein Ziel der zukünftigen Forschung ist die Konstruktion ähnlicher Modelle, in denen Gestalten, auch bei topologischen Transformationen, invariant sind. Solche Modelle könnten im Einklang mit der Forschung zeigen, dass die globale Natur der Wahrnehmungsorganisation anhand topologischer Invarianten beschrieben werden kann. Zur Überprüfung dieser Modelle werden vorhergesagte Beziehungen zwischen den transformierten phänomenalen Gestalten und den neuronalen Mustern der Netzwerkzustände und ihrer Transformationen herangezogen.

Schlüsselwörter: Kategorientheorie, bewusstes Experiment, Emergenz, visuelle Gestalt, wiederkehrende neuronale Netzwerke.

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References

Adámek, J., Herrlich, H. & Strecker, G.E. (2009): *Abstract and concrete categories: The joy of cats.* Mineola, NY: Dover Publications.

Anderson, P.W. (1972): More is different: Broken symmetry and the nature of the hierarchical structure of science. *Science, 177(4047),* 393-396.

Awodey, S. (2010): *Category Theory (Second Edition).* New York: Oxford University Press.

Benjaminsson, S., Silverstein, D., Herman, P., Melis, P., Slavnić, V., Spasojević, M., Alexiev, K., & Lasner, A. (2012): Visualization of output from large-scale brain simulations. Available online at www.prace-ri.eu.

Chalmers, D. J. (1996): *The conscious mind: In search of a fundamental theory.* New York, NY: Oxford University Press.

Chen, L. (1982): Topological structure in visual perception. *Science, 218*(4573), 699-700.

Chen, L. (1985): Topological structure in the perception of apparent motion. *Perception, 14*, 197-208.

Chen, L. (1990): Holes and wholes: A reply to Rubin and Kanwisher. *Attention, Perception & Psychophysics, 47*(1), 47-53.

Chen, L. (2005): The topological approach to perceptual organization. *Visual Cognition, 12*(4), 553-637.

Chen, L. & Zhou, W. (1997): Holes in illusory conjunctions. *Psychonomic Bulletin & Review, 4*(4), 507-511.

de Garis, H., Shuo, C., Goertzel, B. & Ruiting, L. (2010): A world survey of artificial brain projects, Part I: Large-scale brain simulations. *Neurocomputing*, *74*, 3-29.

Deerwester, S., Dumais, S.T., Furnas, G.W., Landauer, T.K. & Harshman, R. (1990): Indexing by latent semantic analysis. *Journal of the American Society for Information Science, 41,* 391-407.

Ehresmann, A, & Vanbremeersch, J.P. (2007): *Memory evolutive systems: hierarchy, emergence, cognition.* Amsterdam: Elsevier.

Kainen, P.C. (1992): Functorial cybernetics of attention. In A. V. Holden & V. I. Kryukov (Eds.), *Neurocomputers and attention: Connectionism and neurocomputers*. Manchester, U. K.: Manchester University Press.

Kalman, D. (1996): A singularly valuable decomposition: The SVD of a matrix. *College Math Journal, 27,* 2-23.

Landauer, T.K., Foltz, P.W. & Latham, D. (1998): Introduction to latent semantic analysis. *Discourse Processes*, *25*, 259-284.

Larson, G.W. & Shakespeare, R.A. (2004): *Rendering with Radiance: The art and science of lighting visualization (Revised Edition).* Charleston, SC: BookSurge LLC.
Laughlin, R. (2005): *A different universe: Reinventing physics from the bottom down.* New York: Basic Books.
Lawvere, F.W. & Schanuel, S.H. (2009): *Conceptual mathematics: A first introduction to categories (2nd Ed.).* New York: Cambridge University Press.
Lehar, S.M. (2003a): Gestalt isomorphism and the primacy of subjective conscious experience: A Gestalt bubble model. *Behavioral and Brain Science,* 26(4), 375-444.
Lehar, S.M. (2003b): *The world in your head: A Gestalt view of the mechanism of conscious experience*. Mahwah, NJ: Lawrence Erlbaum.
Mendelson, B. (1990): *Introduction to topology (3rd Ed.)* New York, NY: Dover Publications, Inc.
Oksala, T. (1979): The language of formal architecture. *Environment and Planning B*, *6*, 269-278.
Pavloski, R. (2006): An attractor lattice model with latent emergent order. *Nonlinear Dynamics, Psychology, and the Life Sciences, 10(3)*, 319-340.
Pavloski, R. (2008): Hidden perspectives in emergent structures produced by neural networks. In S. Vrobel, O. E. Rössler & T. Marks-Tarlow (Eds.), *Simultaneity: Temporal structures and observer perspectives*. Singapore: World Scientific, pp. 286-300.
Pavloski, R. (2010): Searching for a neural isomorph of the perceptual gestalt: From cortical currents to hidden patterns in the dynamics of recurrent neural networks. *Gestalt Theory*, *32*, 115-154.
Pavloski, R. (2011): Learning how to get from properties of perception to those of the neural substrate and back: An ongoing task of Gestalt Psychology. *Humana.Mente Journal of Philosophical Studies, 17,* 69-94.
Rosen, R. (1958a): A relational theory of biological systems. *Bulletin of Mathematical Biophysics*, 20, 245-260.
Rosen, R. (1958b): The representation of biological systems from the standpoint of the theory of categories. *Bulletin of Mathematical Biophysics, 20,* 317-341.
Todd, J.T., Chen, L. & Norman, J.F. (1998): On the relative salience of Euclidean, Affine and Topological Structure for 3D form discrimination. *Perception, 27*, 273-282.
Todorović, D. (2011): What is the origin of the Gestalt Principles? *Humana.Mente Journal of Philosophical Studies, 17,* 1-20.
Treisman, A. & Gelade, G. (1980): A feature-integration theory of attention. *Cognitive Psychology, 12*, 97-136.
Wagemans, J., Feldman, J., Gepshtein, S., Kimchi, R., Pomerantz, J.,R., van der Helm, P. A. & van Leeuwen, C. (2012): A century of Gestalt psychology in visual perception: II. Conceptual and theoretical foundations. *Psychological Bulletin, 138,* 1218-1252.
Wertheimer, M. (1912): Experimentelle Studien über das Sehen von Bewegung. *Zeitschrift für Psychologie, 61,*161-265. (Translated extract reprinted as "Experimental studies on the seeing of motion". In T. Shipley (Ed.), (1961), Classics in psychology (pp. 1032-1089). New York, NY: Philosophical Library.)
Zhou, T., Zhang, J. & Chen, L. (2008): Neural correlation of 'global-first' topological perception: Anterior temporal lobe. *Brain Imaging and Behavior, 2*(4), 309-317.

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