Using Non-Oscillatory Dynamics to Disambiguate Simultaneous Patterns

Tsvi Achler

Abstract— **Simultaneous patterns within images may have conflicting interpretations depending on context (other representations concurrently inferred). This causes significant problems known as 'the binding problem' and 'the superposition catastrophe' for recognition algorithms that incorporate parameter optimization (including neural networks).**

Previously oscillatory dynamics have been proposed to better separate patterns and address such problems. Another dynamic method, independent of oscillation, is proposed that infers which representations fit together.

It works by cycling activation between inputs and outputs. Inputs activate contending representations which in turn inhibit their representative inputs. Inputs utilized by multiple representations are more ambiguous and are inherently inhibited more. The inhibited inputs then affect representation activity, which again affects inputs. The cycling is repeated until a steady state is reached.

This method allows simultaneous evaluation of representations and can determine what set of representations best fit the whole image. The implementation of feedback dynamics for separating patterns is described in detail and key examples are demonstrated by simulations.

I. Introduction

To survive animals must interpret simultaneous patterns (scenes) quickly, e.g.: find the best escape path from an encircling predator pack; identify food in a cluttered forest. Unfortunately, realistic scenes are formed from combinations of previously learned patterns, which often overlap. Simultaneous patterns are also a problem in AI scenarios for example: written words and numbers within a page, scene understanding, and robot disambiguation of sensory information. However animals' abilities are more robust than artificial methods. One possible reason is whether neural network, machine learning, genetic and AI algorithm approaches are employed, most computational algorithms utilize weighted interconnections between nodes to perform recognition. This approach is not optimal for recognizing combinations of previously learned patterns. Two major problems associated with simultaneous patterns are described in the classical literature: 'the binding problem' and 'superposition catastrophe'. To achieve reliable precision given novel combinations, configurations based on optimized connection weights may require an exponential amount of training [1, 2].

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T. Achler is with the Computer Science Department, University of Illinois at Urbana Champaign, Urbana, IL 61801 USA (217-244-7118; fax: 217-265-6591; e-mail: achler@uiuc.edu).

A. Weights and The Binding Problem

The binding problem occurs when image features can be interpreted through more than one representation [3, 4].

An intuitive way to describe this problem is through visual illusions. For example, a local feature can support different representations based on the overall interpretation of the picture. In the old woman/young woman illusion of fig 1, the young woman's cheek is the old woman's nose. Though the features are exactly the same, the interpretation is different. In humans, this figure forms an illusion because all features in the image can fit into two representations. Classifiers have similar difficulties but with simpler patterns. If a pattern can be part of two representations then the networks must determine to which it belongs. Training is used to find optimal interconnection weights for each possible scenario. However, this is not trivial for combinations of patterns and training can grow exponentially.

Fig. 1

B. Weights and The Superposition Catastrophe

The mechanism of conferring recognition based on weights appears to play an important role in algorithms' varied performance between single and novel combinations of patterns. Weight parameters are determined through the training data, requiring the training distribution to be similar to the testing distribution. This allows the correlation between input features and outcomes to be determined through a training set, and learning to occur. However the training distribution is commonly violated in the natural (test) environment, such as a scene or overlapping patterns.

If a network is trained on patterns A and B presented by themselves and they appear side-by-side simultaneously, this is outside the training distribution. Training for every pair of possible patterns (or triplets, quadruplets, etc.) is combinatorially impractical. This combinatorial explosion of training is responsible for the superposition catastrophe [2], and described in early connectionist networks [5].

C. Using Dynamics to Improve Performance

Methods incorporating oscillatory dynamics e.g. [3, 4] have been successful in differentiating components of patterns within a scene and partially addressing these problems, but other dynamic mechanisms are possible.

The focus of this paper is reducing the reliance on parameter optimization in favor of 'feedback homeostasis' methods. Such methods allow networks greater dynamical processing.

D. Motivation of Homeostatic Feedback

Self-Regulatory Feedback Networks (SRFN) are motivated by feedback inhibition, a neural configuration found overwhelmingly throughout the brain. This method of recognition processing is qualitatively described as implementing Self-Regulatory Feedback, because each input is regulated by its own output nodes [1, 6-8]. Though connections are determined by supervised learning, they are not trained in a conventional sense (i.e. through parameter optimization) since there are no connection weights to optimize.

E. Structure Comparison

The difference from neural networks is subtle in structure and notation. Classical neural networks are composed of an input layer, hidden layers and an output layer: x represents activity of input cells, y activity of output cells. Synapse strength is determined by optimized weight w. There is no pre-synaptic inhibition. Other variations of neural networks, such as recurrent networks, may have outputs that are re-used as inputs but are not subject to presynaptic inhibition.

Self-regulatory feedback networks are realized as a two layer network: input layer and output layer, with no hidden units. x represents input activity to input nodes, f represents activity of input nodes, y activity of output nodes. Input activity x drives input node activity f (every x has a corresponding f) which drives output node activity y. However due to pre-synaptic inhibition, output activity y inhibits input activity f. Thus, x excites input node activity while output activity inhibits input node activity. Connectivity strengths are uniform, which means all x's that project to a y have the same weight (similarly all of a y's feedback connections to its x's have the same weight).

Though this structure represents a shift from traditional neural networks, it is a biologically-plausible connectionist network and arguably even more so [9]. It allows information to dynamically flow from input to output and back, determining distributed solutions without optimized parameters.

F. Modularity and Simpler Network Connectivity

A major property is configuration modularity: a network can be composed of simple constructs that can be combined together to interact logically without requiring a-priori declaration of 'interaction-type' connections. Self-Regulatory Feedback Networks only need binary connections and do not require conventional connection weights. This allows simpler training algorithms.

Addition of a new cell to the network only requires that it forms symmetrical connections about its inputs and not directly connect with the other output cells. Thus the number of connections of a specific cell in feedback competition is independent of the size or composition of the classification network, allowing large and complex feedback networks to be combinatorially and biologically practical.

G. Recursive Function

SRFNs use output activation to modify input activation. The modified input activity is then re-distributed to the network determining new output activation. This modification process (feedback) is repeated iteratively to dynamically determine stimuli relevance. In this manner regulatory feedback determines the relevance of inputs to an output node.

This model does not assume calculations are based on predetermined connection weights. All input features are connected equally to associated output nodes. Thus each representation is equally connected to all of its parts. Since connection weights are not relevant, only qualitative relations between feature membership to representation classes need to be determined during setup; e.g. $y_1 \epsilon [x_1, x_3 \ldots]$, $y_2 \epsilon [x_2, x_3 \ldots]$. These represent symbolic-like interconnections.

II. Mathematical Formulation

This section introduces general nonlinear equations governing SRFN. Borrowing nomenclature from engineering control theory, this type of inhibitory feedback is negative feedback, in other words stabilizing, homeostatic or regulatory feedback.

Each neuron is regulated by the post-synaptic use of its

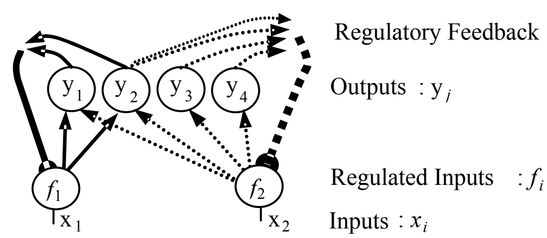

Fig. 2 Self-Regulation: if x_1 affects y_1 & y_2 then pre-synaptic feedback from y_1 & y_2 inhibits x_1. Similarly if x_2 affects y_1, y_2, y_3 & y_4 then feedback from y_1, y_2, y_3 & y_4 regulates x_2

information. The activation of output a is governed by the nonlinear difference equation

$$y_a(t+1) = \frac{y_a(t)}{n_a} \sum_{i \in N_a} f_i \tag{1}$$

with presynaptic inhibition affecting every input b

$$f_b = \frac{x_b}{Y_b} \tag{2}$$

through feedback term

$$Y_b = \sum_{j \in M_b} y_j(t) \tag{3}$$

For any post-synaptic cell y_a, set N_a denotes all its pre-synaptic cell connections and n_a denotes the number of these connections. For any input x_b, set M_b denotes all post-synaptic cells connected to it. The total amount of feedback from post-synaptic cells to input x_b is Y_b. f_b, is the input value after *negative* feedback. Self-Regulatory networks do not rely on weight parameters. Binary connections are sufficient, simplifying connectivity and training. These relations define a negative feedback relationship commonly studied in engineering control theory. Feedback modifies input values. The modified input values are re-distributed to the network and subsequently receive feedback on this re-distribution. The iterative nature allows robust inference during the recognition phase. The outputs y have been shown analytically to be bounded between zero and x values [7, 8] and this class of equations settle to a steady state [10]. These equations implement a multiclass classifier that can process simultaneous patterns [11]. Furthermore, this structure maintains a simple input-output connectivity where each unit connects to its own inputs in a simple manner. Yet the networks make complex recognition decisions based on distributed processing [8].

A. Dynamic Function

The networks dynamically test the input and output of information. Suppose a neuron provides information x_a to its post synaptic cells Y_a. These post-synaptic cells feed back in unison to the pre-synaptic cell x_a and regulate its activity in a 'shunting' fashion $f_a = x_a/Y_a$, whereby inhibition does not completely eliminate an input's activity but reduces it. Value f_a represents the resulting pre-synaptic neuron activity.

The tight association creates a situation where the information x_a can be fully expressed to the output layer only if $Y_a = 1$ (which occurs when inputs and outputs are matched). If several post-synaptic cells are overly active, no post-synaptic cell will receive the full activity of x_a because $Y_a > 1$ thus $f_a < x_a$. Conversely if x_a is not appropriately represented by the network $Y_a < 1$ and the input is boosted $f_a > x_a$. This regulation occurs for every input-output interaction.

Additionally, each output cell strives for a total activation of 1. Thus if an output cell has N inputs each connection contributes 1/N activity. This allows a 'matched' cell to be as active as its inputs.

The networks dynamically test recognition of representations by 1) evaluating post-synaptic outputs based on inputs 2) modifying the next pre-synaptic input state based on post-synaptic use of the inputs 3) re-evaluating post-synaptic outputs based on new pre-synaptic activity. Steps 1-3 represent a cycle which can be iteratively repeated (demonstrated by simulations in section IIIA).

III. Binding Demonstrations

Simple scenarios are presented to show that the equations behave in a manner which is beneficial towards binding. In scenario 1) a larger composition completely overlaps with a smaller composition. The smaller composition is inhibited if the larger's inputs are matched. Scenario 2) demonstrates that compositions of partially overlapping representations can cooperate and/or compete to best represent the input patterns. The equations allow two representations to inhibit a third.

A. Simple Overlapping Composition

This is the simplest example the networks. Such compositions can be created in a symbolic/modular fashion. Suppose a node to represent the patterns associated the letter P and another node represents the patterns associated the letter R. R shares some patterns with P. These nodes can intuitively be combined into one network, by ignoring this overlap and just connecting the network. This defines a functioning network without formally learning how nodes R and P should interact with each other. In other words whether the features in common with R or P should predominantly support R or P or both is determined dynamically during testing (via activation and feedback), not training (i.e. though an a-priori predetermined weight).

The two nodes are connected such that the inputs of y_1 (input pattern 'P') completely overlaps with a larger y_2. But node y_2 also receives an independent input pattern'\'.

Descriptively, y_1 has one input connection, thus by definition its fixed connection weight is one. Its maximal activity is *1* when all of its inputs are *1*. y_2 has two input connections so its fixed input connection weights are one-half. When both inputs ('P' & '\') are *1* the activity of y_2 sums to *1*. Note these weights are predetermined by the network. Connections are permanent and never adjusted. Input cell f_1 projects to both y_1 & y_2, thus receives inhibitory feedback from both y_1 & y_2. Input cell f_2 projects only to y_2 so it receives inhibitory feedback from y_2. This simple example demonstrates when a more encompassing representation will predominate over a smaller representation (without a weighting scheme).

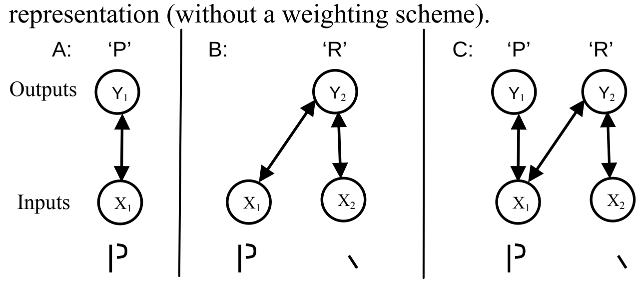

Fig. 3 (A-C): Modular nodes y_1 and y_2 (A & B respectively) can be simply combined to form a combined network (C). Since f & Y are symmetric, the network can be drawn using bidirectional connections.

The equations are:

$$y_1(t+dt) = \frac{y_1(t)x_1}{y_1(t)+y_2(t)} \tag{4}$$

$$y_2(t+dt) = \frac{y_2(t)}{2}\left(\frac{x_1}{y_1(t)+y_2(t)} + \frac{x_2}{y_2(t)}\right) \tag{5}$$

The network solution at steady state is derived by setting $y_1(t+dt)=y_1(t)$ and $y_2(t+dt)=y_2(t)$ and solving these equations. The solutions are presented as (*input values*) → (*output vectors*) in the pattern $(x_1,x_2) \to (y_1,y_2)$. The solutions are $(x_1,x_2) \to (x_1 - x_2, x_2)$. However if $x_1 \le x_2$ then $y_1 = 0$ and the equation for y_2 becomes: $y_2 = \frac{x_1 + x_2}{2}$.

Given R (1,1)→(0,1), given P (1,0)→(1,0). Given only input pattern x_1 ('P') the smaller node wins the competition for representation. Given both input patterns ('P' & '\') the larger node wins the competition for representation.

A simulation showing the steps towards this result yields an intuition about the role of the dynamics. In the simulation of e.g. 1 it is assumed that initially y_1 & y_2 are not very active (y_1 = 0.01 and y_2 = 0.01 at t<1) and inputs become 1 (x_1, x_1 =1 at t=1). *T=0* represents the initial condition (starting state of the network). At *T=1a* the activity of y_1 & y_2 are projected back to the inputs. Both f_1 and f_2 are boosted because representations that use those inputs are not very active. The activation of input nodes f_1 and f_2 are boosted to drive overall activity on the network towards the 'homeostatic' 1. Note that f_2 is boosted twice as much as f_1 because two nodes are using f_1 . Y_1 adds up to twice as much as the inhibitory feedback on Y_2. At *T=1b* the new activation of the inputs is projected to the output nodes. Note that both y_1 and y_2 gain activation. The new activation of the output node is a function of the node's previous activity and the activity of the inputs normalized by the number of node processes. At *T=2a* the activity of y_1 & y_2 are projected back to the inputs again. This time more of f_1 & f_2 are used thus their feedback Y values are closer to 1. Note f_1 <1 and f_2 >1 because two output nodes use the former and one output node uses the latter. From *T=2b* to $T\to\infty$ this trend continues, reducing y_1 activity while increasing y_2 activity. At $T=\infty$ the steady state values of y_1 becomes 0 and y_2 becomes 1.

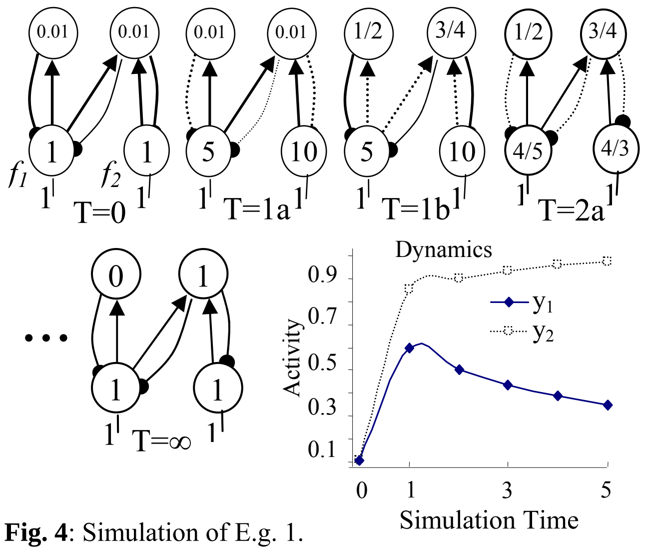

Fig. 4: Simulation of E.g. 1.
Top: *T=0* initial conditions; *T=1a* presynaptic inhibition of inputs; *T=1b* feed forward of modified input activity; *T=2a* next cycle of inhibition; $T=\infty$ activation at steady state.
Right: Graph of y_1 & y_2 dynamics

Thus, if inputs 'P' & '\' are active y_2 wins. This occurs because when both inputs are active, y_1 must compete for all of its inputs with y_2, however y_2 only needs to compete for half of its inputs (the input shared with y_1) and it gets the other half 'free'. This allows y_2 to build up more activity and in doing so inhibit y_1. Though binary inputs were used, the solution is defined for any positive real *x* input values [7].

Thus smaller representation completely encompassed by a larger representation becomes inhibited when the inputs of the larger one are present. The smaller representation is unlikely given features specific only to the large representation. A negative association was implied ('y_1' *is unlikely given feature* 'x_B') even though it was not directly encoded by training.

However in most networks, such associations must be explicitly trained. Such training requires the possible combinations to be present in the training set, resulting in a combinatorial explosion in training.

The Binding and Superposition examples capture these training difficulties.

B. Simultaneous Parts in Binding Scenario

In this composition three representations are evaluated simultaneously. Example 2 is expanded from example 1, with a modular addition of a new output cell y_3. As in e.g. 1, y_1 competes for its single input with y_2. However, now y_2 competes for its other input with y_3 and y_3 competes for only one of its inputs.

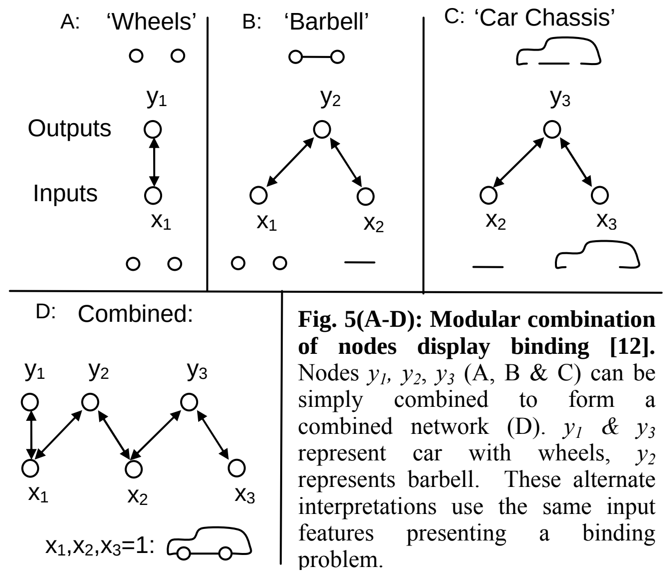

Fig. 5(A-D): Modular combination of nodes display binding [12]. Nodes y_1, y_2, y_3 (A, B & C) can be simply combined to form a combined network (D). y_1 & y_3 represent car with wheels, y_2 represents barbell. These alternate interpretations use the same input features presenting a binding problem.

Equation for y_1 (eq. 4) remains the same as example 1. Equations for y_2 and y_3 become:

$$y_2(t+dt)=\frac{y_2(t)}{2}\left(\frac{x_1}{y_1(t)+y_2(t)}+\frac{x_2}{y_2(t)+y_3(t)}\right) \quad (6)$$

$$y_3(t+dt)=\frac{y_3(t)}{2}\left(\frac{x_2}{y_2(t)+y_3(t)}+\frac{x_3}{y_3(t)}\right) \quad (7)$$

Solving for steady state by setting $y_1(t+dt)=y_1(t)$, $y_2(t+dt)=y_2(t)$, and $y_3(t+dt)=y_3(t)$, the solutions are $y_1=x_1-x_2+x_3$, $y_2=x_2-x_3$, $y_3=x_3$. Thus $(x_1, x_2, x_3) \to (y_1=x_1-x_2+x_3,\ y_2=x_2-x_3,\ y_3=x_3)$. If $x_3=0$ the solution becomes that of e.g. 1: $y_1=x_1-x_2$ and $y_2=x_2$. If $x_2 \le x_3$ then $y_2=0$ and the equations become $y_1=x_1$ and $y_3=\frac{x_2+x_3}{2}$.

Solutions to particular input activations are:
$(1, 0, 0) \to (1, 0, 0)$;
$(1, 1, 0) \to (0, 1, 0)$;
$(1, 1, 1) \to (1, 0, 1)$.
If only input x_1 is active, y_1 wins. If only inputs x_1 and x_2 are active and y_2 wins for the same reasons this occurs in e.g 1. However, if inputs x_1, x_2 and x_3 are active then y_1 and y_3 win. The network as a whole chooses the

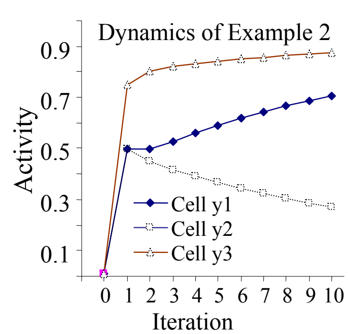

Fig. 6: Simulation of e.g. 2. Graph of y_1 , y_2 , & y_3 dynamics given car (1,1,1).

cell or cells that best represent the input pattern with the least amount of competitive overlap.

As in the previous example, a simulation showing the steps towards this result yields a good intuition about the role of the dynamics.

In e.g. 2, y_2 must compete with all of its inputs: x_1 with y_1, x_2 with y_3. y_3 only competes for half of its inputs (input x_2) getting input x_3 'free'. Since y_2 is not getting its other input x_1 'free' it is at a competitive disadvantage to y_3. Together y_1 and y_3, mutually benefit from each other and force y_2 out of competition. Competitive information travels indirectly 'through' the representations. Given active inputs x_1 and x_2 =1, the activity state of y_1 is determined by input x_3 through y_3. If input x_3 is 0 then y_1 becomes inactive. If input x_3 is 1, y_1 becomes active. However, y_3 does not even share input x_1 with y_1.

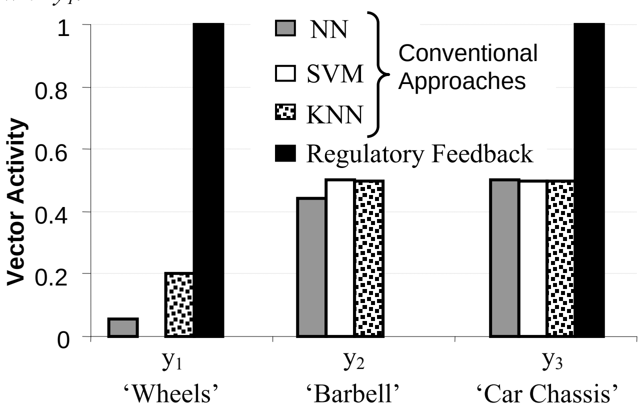

Fig. 7: Binding Problem and Classifier Responses [11]. Neural Networks (NN) and Support Vector Machines (SVM) were trained on the components of fig 5, using the WEKA classifier tool. K-nearest neighbors was determined by the closest neighbor, 1-N. Only Regulatory feedback selects the best fitting pair of representations given the test pattern (1,1,1).

Choosing y_2 given (1,1,1)  is equivalent to choosing the irrelevant features for binding. If the inputs represent spatially invariant features where feature x_1 represents circles, x_3 represents the body shape and feature x_2 represents a horizontal bar. y_1 is assigned to represent wheels and thus when it is active, feature x_1 is interpreted as wheels. y_2 represents a barbell  composed of a bar adjacent to two round weights (features x_1 and x_2). Note: even though y_2 includes circles (feature x_1), they do not represent wheels (y_1), they represent barbell weights. Thus if y_2 is active feature x_1 is interpreted as part of the barbell. y_3 represents a car body without wheels (features x_2 and x_3), where feature x_2 is interpreted as part of the chassis. Now given an image of a car with all features simultaneously (x_1, x_2 and x_3), choosing the barbell (y_2) even though technically a correct representation, is equivalent to a binding error within the wrong context in light of all of the inputs. Most classifiers if not trained otherwise are as likely to choose barbell or car chassis (see figure 7). In that case the complete picture is not analyzed in terms of the best fit given all of the information present. Similar to case 1, the most encompassing representations mutually predominate without any special mechanism to adjust the weighting scheme. Thus the networks are able to evaluate and bind representations in a sensible manner for these triple cell combinations [12].

Similar to the old – woman young woman illusion multiple representations cooperate to interpret the picture. All of the features either are interpreted as a component of either representation (but not confused as a feature of any other representations).

Optimized NN and SVM learning (figures 7 & 9) was performed using the most recent version of the *Waikato Environment for Knowledge Analysis* (WEKA) package [13] currently available (2007). In addition a non-parametric method of K–Nearest Neighbors (KNN, K=1) is compared. It is similar to Adaptive Resonance Theory [14]. Values are determined by the closest input-matching representations to the test pattern. Both y_2 and y_3 were closest and equidistant.

IV. Superposition Catastrophe Demonstration

The Superposition Catastrophe scenario as described by Rachkovskij & Kussul [2] is emulated using letter examples. For intuition purposes the network is tested on letter patterns. Results are similar given randomly generated patterns.

Letter patterns consist of 26 letters of the alphabet, each having a size of 5x5 pixels. These are placed in a visual field, which allows multiple letters to be present at once. The behavior of networks that are only trained with single patterns is evaluated on scenes composed of two and four patterns.

A. Feature Extractor

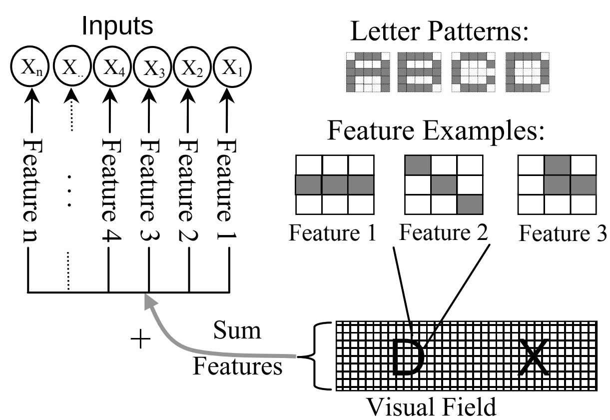

Fig. 8: Feature Extractor. If a feature pattern is present anywhere in the visual field, its feature node's value is incremented. The feature nodes serve as inputs to the classifier.

A simple bag-of-features type feature extractor is applied to all stimuli in the visual field. The extractor is designed to be similar in spirit to the feature extraction found in the primary visual cortex, and is commonly used in cognitive models [15]. It is implemented via a 3x3 pixel binary grid where each possible combination can be a feature (see figure 8). Thus there are 512 possible features. Whenever a feature is encountered in the visual field its count is incremented.

B. Training Without Weight Values

To recognize the 26 patterns, one post-synaptic output cell (y) is designated for each letter. Network 'training' is rudimentary. During learning, when the pattern of a letter is presented to the network, this activates a set of feature input cells. The output cell is simply connected to every feature input cell that becomes activated. Thus each respective output cell is designated to a letter and is connected to all input features activated by the letter pattern. No weights distinguish between the features and each connection has the same connection strength.

C. Results

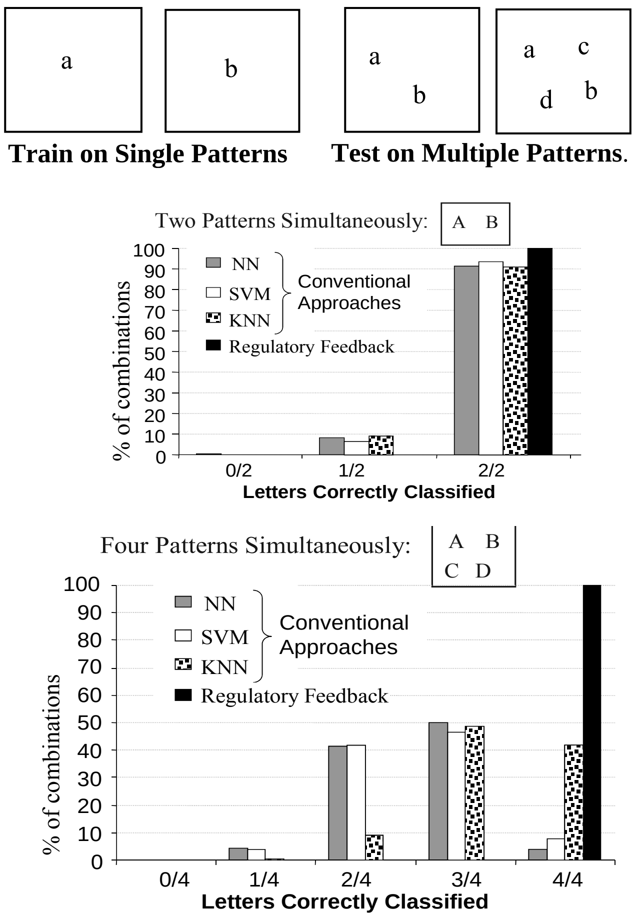

Fig. 9: Superposition Catastrophe Demonstration. Each network is trained on the same single letters and tested on the same combinations of the letters. All possible N-letter combinations are tested. The top n active nodes of each network are selected and compared to the presence of original stimuli. The appropriate n/n histogram bin is incremented. If N=4 letters (bottom) there are 14,900 possible simultaneous 4 letter combinations. Training on ~15k combinations may be required to match accuracy of feedback inhibition.

Algorithms composed of Neural Networks (NN), Support Vector Machines (SVM), and K–Nearest Neighbors (KNN, K=1) are again tested. Each method is given single prototypical representations (features of single letters) for the training phase and tested on multiple simultaneous representations (features of multiple letters summed and presented to the network). Only Regulatory Feedback Networks (based on pre-synaptic inhibition) correctly recognize the simultaneous representations (tested up to eight simultaneous letters and score 100%). This occurs due to nonlinear pre-synaptic feedback, that does not require the training and test distributions to be similar [1].

The examples shown in figure 9 do not have repeating patterns (i.e. two ‘a’s), however this network also computes repeated patterns [16].

This test was repeated with combinations of 30 randomly generated patterns formed from a set of 512 features. For the formation of each pattern each feature had a 50% probability of being on or off. 4 of these 30 patterns are presented simultaneously (810,000 possible combinations). As long as 1) no two representations are the same or 2) two representations do not compose a third, this network recognized all combinations with 100% success.

V. Discussion

These results suggest the root of the difficulties within the Superposition Catastrophe and The Binding Problems may originate from the static nature of parameter optimization.

A. Variable Evidence for Parameter Learning

Commonly neuroscience experiments are cited as evidence of parameter optimization through the idea of Hebbian synaptic plasticity. Synaptic plasticity in this context of learning is the most studied phenomenon in neuroscience. Synaptic plasticity is assumed to occur whenever a long-lasting change in communication between two neurons occurs as a consequence of stimulating them simultaneously. However reliable activity-dependent (Hebbian) plasticity relations have not been determined in adult sensory regions, let alone more complex learning algorithms. The biochemical mechanisms of activity-dependent synaptic plasticity are still unknown because such experiments are variable [9, 17]. Furthermore regulatory feedback networks emulate phenomena seen in experiments (without invoking synaptic plasticity), further questioning biological evidence of such learning [18].

Clearly, robust learning occurs in the brain. However learning rules that are based on connection weights and able to learn any arbitrary pattern may not be warranted biologically.

B. Evidence of Feedback and Pre-Synaptic Inhibition

Alternatives to parameters, such as dynamics, are important. In this work it is suggested that the recursive nature of feedback this allows the networks to disambiguate simultaneous representations. The dynamics seen are similar in gestalt to temporal dynamics in the temporal lobe e.g. [19].

Furthermore, pre-synaptic inhibition and feedback can be found in virtually all areas of brain processing. The thalamic system (including thalamic nuclei the Lateral Geniculate Nucleus-LGN, and Medial Geniculate Nucleus-MGN) projects to the cerebral cortex and receives extensive cortical projections back. Relay cells feed forward to the cortex and pyramidal cells feed back to the cortex. These connections have been described as forming a ubiquitous ‘triad’ structure of regulatory feedback. Furthermore, the thalamus may receive as many connections from the cortex as it projects to the cortex [20, 21].

The mammalian *Olfactory Bulb* (OB), responsible for odors processing, is analogous to the thalamus. It is a separate, modular structure which easier to study. Regulatory feedback modulation of early processing appears not one, but two levels of processing within the OB: 'local' and 'global' circuits.

The local circuit, receives inputs from the olfactory nerve, and connects to mitral/tufted 'output' cells. The output cells simultaneously activate juxtoglomerular cells which pre-synaptically inhibit the olfactory nerve cell axons. The global circuit, receives inputs through the mitral/tufted cells, and 'outputs' to the olfactory cortex. The olfactory cortex projects information back to granule cells within the OB which inhibit the mitral/tufted cells.

Furthermore, nonlinear mechanisms to alter cell activation, based on its previous activity. Such mechanisms can be found within dendritic-dendritic connections involved in coincidence detection (via intercellular NMDA channels). These channels are found in granule cells [22] juxtoglomerular cells [23] of the OB. Together GABA channels (inhibitory connections), calcium & NMDA channels (multiplicative dynamics) and feedback form a regulatory feedback system of inhibition [24, 25]. Thus simulation studies combined with neuroscience experiments reaffirm the ubiquitous presence of feedback and importance of dynamics.

C. Current Model Limitations

The main limitation to this model's applicability is that learning is not as generalizable as conventional algorithms.
In part this is due to the newness of this method and its inherent nonlinearity leading to difficulty deriving general learning rules. It also requires a developing a new set of learning rules that address inherent limits of the model itself. Its limits can be summarized as A) *Generality of Features* where a feature cannot be composed of a mix of existing features and B) *Flexibility of Training*, where currently a general method is not available to train for several versions of the same class.

D. Generality of Features

If the presence of two or more features appearing together define a separate feature, then the network can settle to one of many multiple fixed points (most of which not necessarily the desired recognition outcome). This can be demonstrated with two objects: For example if x_1 and x_2 appearing separately characterizes A and B respectively, and if C is characterized by the presence of x_1 and x_2 together, then the network will yield indeterminate results. The learning algorithm must be able to recognize when these conflicts occur and either redefine features, or increase the dimensionality by adding new features that are linearly independent.

Ideally, the number of dimensions should be greater than or equal to the number of objects to classify and count. A generic method for defining features or boosting the number of dimensions is the subject of a future study. However the features should be designated so that each feature corresponding to class is linearly independent from the rest, as is the case for the extractor implemented in this paper.

E. Flexibility of Training

Even though this architecture can cope with noisy data [11] currently an analytical method to learn variants of characteristic patterns (such as different fonts) is not available. Solving deriving a general analytical solution is difficult because the networks are nonlinear.

Modularity properties allow the simple training scheme used in this paper which consists of forming binary connections according to a single sample. One way of extending the training algorithm to data with more variation is by introducing extra layers to the network; whenever the network comes across a drastically different rendition of a letter, say **B** instead of $\mathcal{B}$, it could form a new node and dedicate this to the different rendition, $y_{\mathcal{B}}$ and then connect this to the node that corresponds to the usual rendition $y_{\mathbf{B}}$ in a hierarchical fashion. This way activity in either $y_{\mathcal{B}}$ or $y_{\mathbf{B}}$ will stimulate a third node that corresponds to the idea of B. Another way of extending training is through clustering methods which can take several data points and produce an averaged prototype. Learning algorithms to capture data variation and structure, exploit modularity properties and avoid parameter optimization are the subject of future work.

F. Combined Oscillatory and non-Oscillatory Dynamics

Like conventional methods, the regulatory feedback method may be used along with oscillatory methods as well. Oscillatory activation can cause both feed forward and feedback activation, possibly even generating non-oscillatory activity.

G. New Neural Paradigm

In summary, this work suggests that the 1) brain may not function via optimized parameters 2) Self-Regulatory Feedback is a major contributor to flexible processing and binding. The feedback perspective may lead to a better understanding of animals' ability to efficiently interpret simultaneous patterns.

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