Randomization and Selection of Self-Calibrating Binary Encoders in Neural Systems

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Randomization and Selection of Self-Calibrating Binary Encoders in Neural Systems

Short Title: Brainy Bits

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Abstract

Zebrafish larvae are able to track and capture prey five days post-fertilization, consistent with a genetic specification of pattern recognition by the nervous system, yet inconsistent with a process that involves tweaking of individual neural connections by processes similar to those currently employed to train artificial neural nets (ANN). Biological neural networks appear extremely efficient and adaptable when compared to ANN. Here I describe self-calibrating randomly initiated binary encoders (SCRIBEs) that produce sparse output and are highly scalable. The self-calibrating nets (SCN) they generate are capable of classifying and tracking objects with high accuracy and fluency by a process based on selection of SCRIBE arrays optimizing survival. Calibration of SCRIBEs depends on array thresholds that vary with their size but can happen without external input during development and sleep. In neural systems, synchronization likely depends on neuromodulator and brainwave status.

ANN represent a significant advance in processing complex data but have a large computational cost, far beyond the capacity of a genome to encode all the steps involved and for cells to perform all the computations necessary to optimize outcomes in environments that change rapidly. Neural nets in these systems rely on adjusting weights of connected nodes to distinguish input features. Learning times are long. For example, the convolutional neural network (CNN) LeNet5¹ requires 6 layers with thousands of parameters to achieve high accuracies and multiple epochs of training to maximize performance and accuracy, as do many other ANN designs.^{2,3}

SCRIBEs offer an alternative approach that matches what is known about the biology. They are based on variably sized neuronal arrays with n nodes that self-calibrate in the absence of external inputs. The self-calibration process in this model resembles that observed in animals like the ferret where development of the visual system is synchronized by brainwaves spontaneously generated within the retina.⁴ SCRIBE architecture is well-defined (Figure 1). The rules for generating the design could be genetically programmed and recursive, like those for specifying cellular automata, with outcomes over time subject to natural selection.^{5,6}

SCRIBE S-arrays described here potentially have n input and n output nodes. The initial probability of connection p_{ij} between the input and output nodes is given by a randomly assigned $n \times n$ transition matrix with $0 < p_{ij} < 1$, where matrix rows correspond to input nodes and columns to output nodes (Figure 1A, Supplementary Figure 1). The S-arrays then undergo self-calibration in the absence of any external input through a recursive Markov process, ending when the transition matrix reaches a stationary value (Chapman-Kolmogorov Theorem). The approach used here differs from the usual Markov implementation. A threshold t is applied at each step of the calibration process, below which p_{ij} is set to zero. This constraint results in connection probabilities between input and output nodes of either 0 for values less than or equal to t , with the constraint that row probabilities sum to 1. Once fully calibrated and due to the random nature of their initiation, the arrays generated have a variable number of active

input nodes. The number of output nodes also varies. Above a certain value of t , some arrays become binary encoders, mapping active input nodes to one of the n possible output nodes with equal probability. (Figure 2). These arrays have n potential outputs, an outcome with far much less complexity than the 2^n combinations present in uncalibrated arrays. After calibration, multiple inputs to a SCRIBE are then reduced to a single output. The sparsity produced simplifies downstream processing in an information saturated environment.

The effects of varying t on the calibration of a $n = 4$ SCRIBE array are illustrated in Figure 2A. At $t = 0$, all nodes are connected, with all rows and columns active. When $t = 0.47$, only a single output is produced from 33% of the arrays, with two active nodes in 1% of arrays (referred to as t_1). At thresholds just above t_1 , there are many active arrays with a single output. As t becomes higher, the number of active arrays decreases, sparsifying the output from a receptive field further (Figure 2A). When $t = 0.9$, there is no output as nodes are disconnected and there is no flow of information to downstream processes.

Threshold effects found for SCRIBEs of $n=4$ are observed for all array sizes tested and scale by $t_1 \approx \sqrt[3]{2}/(n + 1)$ (for $n>3$) (Figure 2B). The maximum size of arrays is limited by t_1 , which must be high enough to prevent spurious activation (i.e. $t > t_0$, where t_0 is the minimal activation potential for a node). The binary output from the self-calibrated arrays represent the presence or absence of a feature specified by the inputs. In contrast, ANN use processes like back-propagation to identify features in the data *de novo*.⁷ In biology, these feature sets have already undergone selection during evolution.

Once S-arrays are self-calibrated, feature detection depends on the orientation of the sensory neurons that provide input from the milieu to the arrays. The active input nodes vary between calibrated S-arrays, reflecting the random initiation process. Consequently, each array will extract slightly different feature information from the receptive fields they share. The physical area from which they derive their sensory input reflects an object's size. The fraction of arrays active at one instant will also differ between arrays

from the same receptive field. Those S-arrays with a small number of tightly clustered inputs may produce output at one moment, while those with more diffusely spread inputs fire at different times. The difference permits discrimination of feature attributes like loud relative to soft and bright relative to dark. While the feature detected by the different arrays remains the same, each feature attribute receives a different binary encoding. Collectively, the detection of multiple feature attributes enhances feature detection in noisy environments.

Once self-calibration is complete, neighboring arrays with the same architecture and sensory input detect the same data feature, but differ in the node they use for output. If all array outputs converge on the same set of downstream neurons, the redundancy will ensure that feature detection is robust as loss of output from a particular array does not cause failure. Alternatively, the projection of the various array outputs to different brain regions would enable multiple different strategies for feature classification. Other options also exist. For example, outputs from a particular ordinal position of an array could activate downstream inhibitory neurons, while outputs from other positions are programmed to synapse with excitatory neurons. Collectively, the positive and negative assignments to the binary outputs from different nodes can help define the receptive field for a feature. Such effects mirror those discovered in the analysis of the cat visual cortex⁸ and zebrafish visual system.⁹

Collectively the binary outputs from a collection of self-calibrated S-arrays provide a barcode representation of their inputs, enabling object classification (Figure 3). This process can be modeled by using self-calibrated nets (SCNs) as defined further in Supplementary Methods. In the example presented, efficient classification of handwritten digits is achieved with an accuracy exceeding 99.6% for the MNIST dataset and around 97.5% for the US Postal number collection, both measures consistent with human capabilities.^{2,10} The best classifiers obtained by these SCNs require very few parameters (ranging as low as 67 in this case), rather than the many millions found optimal for some ANN¹¹. One reason for the different efficiencies is that SCNs have no need for weights assigned to each output node, nor for back-

propagation. Another reason is that SCN learning occurs at the level of the classifier. The process is facilitated by the sparsity of SCRIBE outputs described above. The most basic classifier just drops those features that discriminate poorly between objects.

Thresholds far above t_1 yield only a small subset of active self-calibrated S-arrays. Other arrays with similar architecture are rendered silent, reflecting the random assignment of p_{ij} preceding calibration (Figure 2 and Supplementary Figure 2). The sparsity of active arrays facilitates downstream processing of input data. It also generates an index for integrating features detected by other arrays into the classifier. Training multiple sparse classifiers in parallel, with each acting independently of the other, additionally improves recall efficiency when new images are presented (Supplementary Materials). Multiple classifiers not only enhance accuracy, but also improve performance by reducing interference from objects with similar features.¹² While voting algorithms represent one approach for choosing the best classifiers from many, other algorithms may offer rule-based solutions that combine the best features of individual classifiers and avoid the local minima encountered by each that lead to higher misclassification rates.¹³ As such heuristics undergo evolution, the simple, species-specific, context-dependent algorithms leads to abstract representations to better shape the input data in ways that promote survival.¹⁴

SCRIBEs potentially enable abstraction by feed forward mechanisms. These allow the programmed recruitment of randomly initiated arrays (R-arrays) to measure spatial and temporal variations in the input data. In the scenario outlined in Figure 1, self-calibrated S-arrays synchronize a set of R-arrays to produce tracking arrays (T-arrays) that follow the feature initially detected by the S-array as it moves across receptive fields (Figure 1C and 1D). Some possible functions of T-arrays are illustrated in Figure 1 e, f and g. The tracking of a feature's translation and rotation directly measure the speed and direction of its movement (Figure 3B and 3C). The variations in T-array size further enable gradient mapping and estimates of an object's size. These measures are based on the sequential activation of small T-arrays (present in *boxes 1, 2 and 3* of Figure 3D) within the receptive field of a larger T-array. The same process

establishes the sequence of events. The definition of spatial borders, delineation of surface features and different temporal progressions promotes object fluency. Self is then separable from non-self as is cause from effect.

Setting of T-array by S-arrays is likely fast as this enables survival in a constantly changing environment. Synchronization is achievable in a number of ways. For example, brainwaves of a particular frequency or intensity could set t to initiate binary encoding by T-arrays within a certain size range. Support for such a rapid process is provided by the evidence for neuronal avalanches¹⁵ and for self-organized criticality.¹⁶ The feed forward mechanism tracks future inputs by the features followed.

Systems based on SCRIBEs do have limitations. One problem arises when outputs from arrays are incongruent, as occurs with the Stroop test, where the color of a word differs from the color it describes. The optimal classification then depends on context with only one option better than the other. Another limitation occurs when repetitive input locks T-arrays onto a particular feature, hindering the ability to track other object characteristics. One solution to prevent prolonged lock in of arrays to repetitive stimuli relies on habituation: features that remain constant are no longer tracked. Alternatively, another set of R-arrays could be synchronized to track a different set of time varying features. A further potential issue concerns the time it takes for T-arrays to desynchronize after a particular input is no longer present. The persistence time of a particular set of synchronized T-arrays then depends on processes such as long-term potentiation and depression.¹⁷

One way to minimize the risk of sub-optimal outcomes is through the frequent, programmatic resetting of T-arrays. Re-initiation of arrays could be forced by raising t high above t_1 to desynchronize the arrays or by lowering t to t_0 to return arrays to their initial random, unsynchronized state (Figure 2A). Neuromodulation of t_1 is also an option, with the differential expression of neuromodulator receptors allowing targeting of specific T-array subsets.¹⁸ Recalibration of S-arrays could occur during system sleep,¹⁹

119 when S-arrays are isolated from external inputs. Sleep could reinforce the selection of S-array sets specific
120 for features frequently present in a particular environment, altering the repertoire of S-arrays available
121 for feature detection, enhancing the performance of the sparse classifiers that underlie object fluency.
122 The act of sleep thereby changes the perception of what is possible upon waking.²⁰

123 The sparse coding of input by SCRIBEs enables the evolution of designs that are time and energy efficient
124 with low Kolmogorov complexity due to their sparsity.²¹ Better representations of the environment
125 improves the anticipation of subsequent events. The evolution of binary classifiers described here
126 progresses from SCRIBEs to SCNs, improving survival stepwise in constantly changing, overwhelmingly
127 feature-rich environments. Abstraction is an emergent property of the classifiers involved, further
128 enhancing the adaptability of an organism to different threats. The process depends on the randomization
129 and selection of SCRIBEs. The simple architecture of SCN allows for their genetic specification, offering up
130 a possible explanation for why Zebrafish larvae can track and capture prey forty-eight hours after
131 hatching.⁹

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Figures

Figure 1. Self-calibrating arrays (S-arrays) synchronize random arrays (R-arrays) to produce synchronized T-arrays detecting the same feature. The colored round-cornered boxes represent arrays with n input and n output nodes. The number p_{ij} represents the probability of node i connecting to node j is. **A.** S-arrays self-calibrate via a recursive Markov process, with outcomes dependent upon the threshold t below which p_{ij} is set to zero. The threshold t can be set by neuromodulators or by brainwaves tuned to a particular subset of arrays. A binary output from a single node is produced when $t > t_1 > t_0$ where t_1 is scale free, varying by $1/(n+1)$ and t_0 is the minimal activation potential for node n . At sufficiently high values of t , arrays with have no active output. **B.** Following calibration, S-arrays map multiple inputs from external data to a single output. **C.** The output from S-arrays then synchronizes uncalibrated randomly initiated R-arrays to produce a set of T-arrays that detect the same feature in the input data as the S-array. **D.** The T-array are orientated in various direction and allow tracking of the specified feature over time and space **E.** T-arrays can detect translation of an object across receptive fields. **F.** T-arrays can also track the rotation and direction of movement of an object. **G.** The output from smaller sized arrays helps in detecting object borders and gradients within the receptive field of the larger array, ensuring fluency in object tracking and any of its other associated features. Here changes to the output from smaller T-arrays present in boxes 1, 2 and 3 reflect the movement of an object relative to the receptive field of the larger array and provide a measure of its scale. Collectively the outputs from T-arrays help separate self from non-self. The feed forward mechanism anticipates future inputs. Feedback mechanisms enhance the selection of S-arrays that respond best to features frequently present in a particular environment.

Figure 2. The output of S-arrays is determined by the threshold t , below which the probability of connection between nodes p_{ij} is set to zero. Self-calibration continues until a steady state is reached. For the data presented here, the initial values for p_{ij} are randomly set. Consequently a number of arrays reach a steady state with a zero output, while others stabilize with a single active output node to become binary encoders. **A.** The effect of different values t on the input and output of a 4 x 4 array. For $t = 0.45$, 33% of arrays have a single output with only 1% having two active output nodes (defined as t_1). **B.** Thresholds for S-arrays with different node numbers, showing the percent of arrays with output from a single node when $t = t_1$. As the S-array size increases, t_1 decreases as does the percent of arrays with a single output. Arrays with zero output can be reinitiated with new randomly set values for p_{ij} and restart the self-calibration process. (Supplementary Figure 2 displays the effects of varying t for S-arrays with different node numbers).

Figure 3. Example of a self-calibrating network (SCN) for the MNIST and USPS sets of hand-written digits. The outputs from SCRIBES are classified using a design inspired by previous work on Convolutional Neural Networks (CNN). The approach differs from CNN because the input derives from the binary representation of image features by SCRIBES, with the presence or absence of each feature reported. The outputs associated with each image are processed in parallel (described in Supplementary Methods). The stacked, barcoded features corresponding to a collection of images are classified using L1 regularization to minimize the number of non-zero (NZ) coefficients. The barcode for the image shown is bounded by the red box and is incorporated into the stack classifier along with other barcoded images. The data shows results from analysis of hand-written digits from the MNIST and USPS datasets (<http://yann.lecun.com/exdb/mnist/>) using the training and test sets provided. In each analysis, multiple SCNs were used in parallel. Each SCN used as input images that had been rotated to give different perspectives. The output was convoluted with SCRIBES tuned to different binary features of the pre-processed images. The set of SCRIBES used for the convolution is referred to as a kernel. The SCRIBES in each kernel were randomly selected. The number of SCRIBES in a kernel was also varied. For each analysis, the mean accuracy is presented, along with the values for the best and worst SCRIBE results. The lowest number of NZ classifiers is presented demonstrating the efficiency of the approach from a biological perspective. The accuracies obtained are equivalent to those obtained with human subjects.

Supplementary Figure 1

The transition matrix S_n for S-arrays of size n is derived using a Markov Process that after m iterations reaches a steady state with row probabilities that sum to 1. The value of p_{ij} is adjusted at each iteration according to the constraint.

A. $N=3$

B. N=5

C. N=6

D. N=7

Supplementary Figure 2. Threshold effects on SCRIBE Arrays that vary in size. A plot of the percent of active inputs (in grey) and active outputs with arrays composed of n input nodes and n output nodes. Thresholds are varied from $t=0$ to 0.9 for $n=3,5,6$ and 7. Connections below t are set to zero. A 100 cycles of self-calibration were performed.

Supplementary Files

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