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Unsupervised Non-Linear Neural Networks Capture Aspects of Floral Choice Behaviour

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Abstract. Two unsupervised neural networks were tested to understand the extent to which they capture elements of bumblebees' unlearned preferences towards flower-like visual properties. The networks, which are based on Independent Component Analysis and Feature-Extracting Bidirectional Associative Memory use images of test-patterns that are identical to ones used in behavioural studies. While both models show consistency with behavioural results, the ICA model matches behavioural results substantially better in terms of image reconstruction quality of radial and concentric patterns, and foliage background. Both models generated a novel prediction of an interaction between spatial frequency and symmetry. These results are interpreted to support the hypothesis that flower displays are adapted to pollinators' information processing constraints.

1 Information Processing in Bumblebees

Bees use visual information to discover their first rewarding flower, but it's not clear how the visual system aids in this discovery. Hymenoptera species including bumblebees and honeybees are frequently studied to investigate information-processing biases of the visual system. Unlearned visual preferences by bees are usually studied by decomposing a natural flower into its visual constituents and pitting two or more visual properties against one another in choice experiments [1]. Some of the studied components include colour [2], shape [3], symmetry [4], foliage background complexity [5], and pattern positioning [6].

Unlearned floral preferences have been tested in many pollinator species, but the idea that the preferences are a by-product of the information processing properties of environmental information has only been recently suggested [7]. Nectar guides (i.e. radial, sunburst pattern) and floral symmetry are often suggested to be an adaptation, but the distinction of whether the adaptation belongs to the plant or the pollinator, or both, is not specified. Our hypothesis is that nectar guides and symmetric floral displays are an adaptation by the plant to exploit a information-processing constraints in pollinators' nervous system.

The focus of this paper is to compare empirical results with unsupervised neural networks in relation to (a) pattern shape and positioning, (b) foliage background and (c) symmetry and spatial frequency. The networks are evaluated by generating filters from experimental stimuli that are identical in appearance to those used in behavioural studies.

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2 Model Descriptions

There are numerous unsupervised non-linear neural networks that capture various aspects of low level visual processing with good results [8]. We test two algorithms here, Independent Component Analysis (ICA), and Feature-Extracting Bidirectional Associative Memory (FEBAM), which are biologically inspired, and detect local components in images of natural scenes with high performance. Both neural networks accomplish perceptual feature extraction in an unsupervised fashion to keep useful information and discard noise.

2.1 Independent Components Analysis

ICA can be performed on natural images by processing the observed signal in a statistical generative model, the components of which yield a representation of the original data [9]. The process is applied to centered [10] principal components of grayscale image patches, extracted from the source image. Figure 1 shows the architecture of the this neural network, based on Independent Components Analysis.

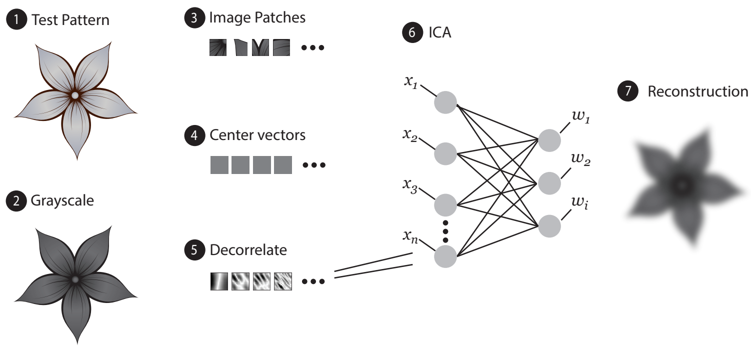

Fig. 1: Network 1 Architecture: ICA

ICA input mixture signals were grayscale 3 x 3 image patches generated from a 100 x 100 pixel byte level image. After centering the image patch vectors, principal components analysis (PCA) was performed on each image to decorrelate the signal. The principal components were used in the ICA dimensionality reduction to 3 components. Deflation fixed-point ICA with tanh function to minimize mutual information was used. Independent components were generated using the fastICA algorithm implemented in Mathematica [11].

Using the inverse of the estimation matrix $\mathbf{W}$, radial and concentric test pattern images were reconstructed. Here $\mathbf{x}$ refers to the test pattern or floral test images, and $\mathbf{y}$ is the matrix of statistically independent component vectors.

$$\mathbf{y} = \mathbf{W}\mathbf{x} \tag{1}$$

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The image $\mathbf{x}'$, was reconstructed using:

$$\mathbf{x}' = \mathbf{W}^{\mathbf{T}}\mathbf{y} \tag{2}$$

2.2 Feature-Extracting Bidirectional Associative Memory

FEBAM is a modified version of the Bidirectional Associative Memory (BAM) [12] where one set of connections were removed. Therefore, the network acts as an unsupervised associative memory. Figure 2 shows the architecture of the second neural network:

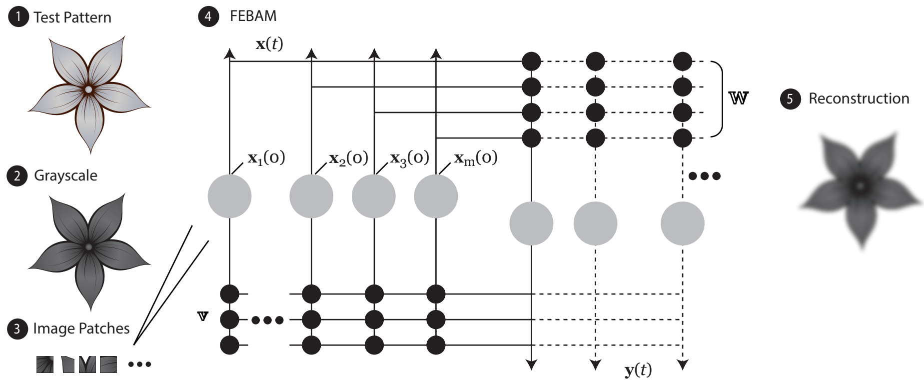

Fig. 2: Network 2 Architecture: FEBAM

The $\mathbf{W}$ weights send information to the output layer, and the $\mathbf{V}$ weights send information back to the x-layer in a top-down bottom-up manner. Activation is expressed by the following relations:

$$\mathbf{y}(t+1) = g((\delta+1)\mathbf{W}\mathbf{x}(t) - \delta(\mathbf{W}\mathbf{x})^3(t)) \tag{3}$$

$$\mathbf{x}(t+1) = g((\delta+1)\mathbf{V}\mathbf{y}(t) - \delta(\mathbf{V}\mathbf{y})^3(t)) \tag{4}$$

where $\mathbf{W}$ and $\mathbf{V}$ are weight matrices, $\mathbf{y}$ refers to the distributed filters across the units, $\mathbf{x}$ is the original image input, and the reconstructed image is $\mathbf{y}$. δ is a general output parameter that determines the type of attractor the network will exhibit (fixed-point, cyclic, chaotic). This value was held constant in this implementation at 0.1 to produce fixed-point attractors. The output of the piecewise function g behaves like a sigmoid-type function, but without the asymptotic property:

$$g(z) = \begin{cases} +1, & \text{If} \quad z > 1 \\ -1, & \text{If} \quad z < -1 \\ & z, \text{Else} \end{cases} \tag{5}$$

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2.3 Outcome Measure

The quality of the reconstructed image was compared to the original image using Peak-Signal-to-Noise-Ratio [13]. The rationale for choosing this measure is that reconstruction quality of images may indicate the cognitive cost to process the test patterns. All parameters kept constant across simulations, better quality of reconstruction means that a fixed number of filters (i.e., 3 filters for both ICA and FEBAM) captured more relevant information to reconstruct the image. Therefore, we suggest that the inherent characteristics of test patterns are computationally more affordable to process and thereby should be more preferred by pollinators, provided prior reward has not been associated with any other visual property.

3 Simulations

Three categories of images were used. First, test patterns manipulating pattern positioning and pattern type, which are identical to ones used in behavioural experiments. Second, test patterns manipulating symmetry and spatial frequency that are also identical to those used in behavioural experiments. And finally, images of natural flowers, with and without a green foliage background that mimic the test patterns used in behavioural studies. All simulations were performed 50 times.

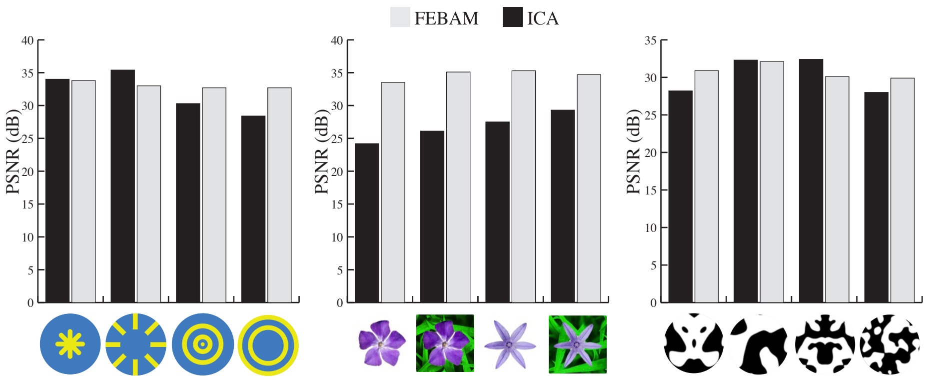

Fig. 3: PSNR reconstruction values for pattern type and positioning, foliage background, and symmetry vs spatial frequency.

3.1 Effect of Pattern Type and Pattern Positioning

Most behavioural studies documented a clear preference for radial patterns (i.e. sunburst-like pattern) over concentric patterns. ICA and FEBAM networks show similarities and differences: overall, radial patterns are better reconstructed than concentric patterns (see Figure 3). Best quality reconstruction is achieved by

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the peripheral radial pattern using ICA, and the central radial pattern using FEBAM. In between are the peripheral radial pattern and the central concentric pattern. The quality differences in FEBAM are very small, but ICA shows substantial quality differences in the direction of behavioural realism.

3.2 Effect of Foliage Background

The role of background in floral preferences has been well documented with one recent study showing preferences towards foliage backgrounds [5]. As with pattern type and positioning, ICA and FEBAM results also show similar results for bilaterally symmetric purple flowers with and without foliage background (see Figure 3). Comparing foliage background with white background, ICA filters reconstructed flowers with foliage background in better quality. Even though overall, the quality of FEBAM reconstructions were better, only one of the flowers was reconstructed in the predicted direction.

3.3 Effect of Symmetry and Frequency

ICA and FEBAM systems produce corresponding but unexpected results when we manipulated symmetry and spatial frequency (3). Behavioural studies are mixed in terms of symmetry preferences, but the methodology of those that do show a preference have been criticized [4]. Both FEBAM and ICA show corresponding results. The test pattern of high spatial frequency show better reconstruction for the bilaterally symmetric version when compared with high spatial frequency asymmetric pattern. However, the low spatial frequency patterns show the opposite trend: the asymmetric pattern had a better reconstruction quality then the symmetric pattern. Perhaps the mixed behavioural results can be explained by an interaction of spatial frequency and symmetry that has not been explored before.

4 Discussion

Both unsupervised non-linear neural networks show a great degree of consistency with behavioural results of unlearned floral choice by bumblebees and honeybees. The results of ICA are more robust because it captured subtler findings related to floral positioning, and more consistency over multiple flowers with foliage background. This may be an indication that each of these models capture a key biological element in the way these pollinators process and respond to visual information. The results lend support to the idea that bumblebees and honeybees show a behavioural preference towards the tested patterns as a result of a by-product in their visual information processing systems.

In terms of future behavioural work, partial consistency with symmetry and spatial frequency produces two hypotheses that could be tested. First, low frequency symmetrical patterns should be preferred over high-frequency symmetric patterns, and even more interestingly, an interaction between symmetry and spatial frequency could be tested. Half of a symmetrical pattern's information may

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be discarded while still coding all relevant information. The interaction may indicate a ceiling in the amount of information that bees' visual system can code.

The neural networks could also be further tuned to simulate the physiological properties of different pollinators visual systems. For example, instead of using byte level information from the image, Liu and Cheng [14] suggests summarizing independent channels using histogram information, which is a statistically more meaningful representation.

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