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Biologically Inspired Pattern Recognition for Robust MIMO Signal Detection Using Convolutional Neural Architectures

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ABSTRACT

Modern MIMO (Multiple-Input Multiple-Output) signal detection faces increasing challenges due to high-dimensional interference, nonlinear channel effects, and noise uncertainty. Inspired by biological signal processing mechanisms observed in neural, sensory, and genetic systems, this work explores convolution-based modeling and neural network architectures for efficient MIMO detection within a pattern recognition framework. In this context, received MIMO signals are treated as high-dimensional patterns, and detection is formulated as a nonlinear classification and decision-boundary adaptation problem. Biological systems inherently perform parallel convolution, distributed feature extraction, adaptive filtering, and noise-robust pattern discrimination properties that closely resemble MIMO communication channels. By mathematically modeling these biological processes using convolution operators, stochastic difference equations, and adaptive learning dynamics, this study establishes formal analogies between synaptic transmission, sensory coding, genetic regulatory networks, and pattern-based MIMO detection frameworks. Theoretical guarantees on convergence, stability, and error minimization are derived using optimization theory, probabilistic bounds, and Lipschitz-based stability analysis. The proposed biologically inspired pattern recognition models exhibit enhanced robustness to noise, scalable detection in large antenna systems, and adaptive decision boundary formation, making them well suited for next-generation wireless communication systems.

AMS Subject Classification: 39A30, 94A20, 39A99

II Mathematical Formulation

2.1 Neural Synaptic Transmission ↔ MIMO Convolution Model

Neurons integrate multiple synaptic inputs through dendrites using weighted summation and temporal convolution [5, 6].

Mathematical model:

$$y_i(t) = \sum_{j=1}^{N} \int h_{ij}(\tau)\, x_j(t-\tau)\, d\tau + n_i(t) \quad (1)$$

where,

$x_j(t)$ - pre-synaptic input (transmitted signal)

$h_{ij}(\tau)$ - synaptic impulse response (channel kernel)

$y_i(t)$ - post-synaptic response (received signal)

$n_i(t)$ - biological noise (thermal/channel noise)

MIMO equivalence:

$$\mathrm{y}(t) = \mathrm{H}(t) * \mathrm{x}(t) + \mathrm{n}(t)$$

This equation directly maps synaptic convolution to MIMO channel convolution [8, 9].

2.2 Visual Cortex Receptive Fields ↔ Convolutional Neural Network (CNN) based MIMO Detection

Neurons in the visual cortex respond selectively to spatial patterns using localized receptive fields.

Mathematical formulation:

$$z_k = \sigma\left(\sum_{m=1}^{M} \mathrm{W}_k * \mathrm{Y}_m + b_k\right) \quad (2)$$

where,

W_k - receptive field kernel

$\sigma(\cdot)$ - nonlinear activation

Y_m - received antenna signals

CNN-based MIMO detectors treat antenna streams as feature maps and learn spatial interference patterns.

2.3 Auditory Signal Processing ↔ Adaptive Noise-Robust Detection

The auditory system filters noise using adaptive frequency-selective convolution [1].

Mathematical model:

$$\hat{x}(n) = \arg\min_{x} \mathbb{E}[\| y(n) - h(n) * x(n) \|^2]$$

This mirrors minimum mean square error (MMSE) based convolutional MIMO detection, where adaptive filters evolve similarly to cochlear filters [4].

2.4 Genetic Regulatory Networks ↔ Iterative Neural Detection

Gene expression levels evolve based on delayed feedback and nonlinear interactions [7, 15].

Difference equation model:

$$x(n+1) = f\big(x(n)\big) + \sum_{k=1}^{K} a_k \, x(n-k) \tag{3}$$

Iterative neural detectors update symbol estimates using memory and feedback similar to gene regulation with delays [12].

III Theoretical Foundations

Theorem 3.1: Convergence of Neural MIMO Detector: Let the neural network-based MIMO detector be trained using a convex loss function $L(\mathrm{x})$ with bounded convolution kernels. If the learning rate satisfies $0 < \eta < \frac{2}{\lambda_{\max}}$, then the iterative detection algorithm converges to a local minimum of L.

Theorem 3. 2: Noise Robustness via Biological Convolution: Let a noisy biomedical signal be modeled as

$$x(n) = s(n) + \eta(n)$$

where $s(n)$ is the true physiological signal and $\eta(n)$ is zero-mean white noise with variance σ^2.

If $x(n)$ is processed by a stable linear difference equation system with impulse response $h(n)$, then the output noise variance satisfies

$$\mathrm{Var}[y(n)] = \sigma^2 \sum_{k=0}^{\infty} | h(k) |^2$$

and is finite.

Proof: If the channel impulse response satisfies $\parallel h \parallel_2 < \infty$, then the convolution-based MIMO detector minimizes the mean square error under additive Gaussian noise. The output due to noise alone is

$$y_\eta(n) = \sum_{k=0}^{\infty} h(k)\eta(n-k)$$

Since $\eta(n)$ is zero-mean white noise [13],

$$\mathbb{E}[\eta(n-k)\eta(n-m)] = \begin{cases} \sigma^2, & k = m \\ 0, & k \neq m \end{cases}$$

Thus, the variance of the output noise is

$$\mathrm{Var}[y(n)] = \mathbb{E}\left[y_\eta^2(n)\right] = \sum_{k=0}^{\infty} h^2(k)\, \mathbb{E}[\eta^2(n-k)] \tag{4}$$

$$= \sigma^2 \sum_{k=0}^{\infty} \mid h(k) \mid^2$$

Since the system is stable, $h(k)$ is absolutely square summable, making the variance finite [11, 14].

Discrete Brain-Inspired Pattern Recognition Model

Consider a neural network with N neurons. Let

$$\mathrm{x}(n) = [x_1(n), x_2(n), \ldots, x_N(n)]^T$$

denote the network state at iteration n. The update rule is [3, 16]:

$$x_i(n+1) = \phi\left(\sum_{j=1}^{N} w_{ij}\, x_j(n)\right) \tag{5}$$

where,

w_{ij} are synaptic weights,

$\phi(\cdot)$ is a nonlinear activation function (e.g., sign or sigmoid).

This represents a brain-inspired pattern recognition system.

Theorem 3.3: Energy Minimization in Brain-Inspired Pattern Recognition: For a symmetric weight matrix $W = [w_{ij}]$ with zero diagonal entries, the neural update rule

$$x_i(n+1) = \operatorname{sgn}\left(\sum_{j=1}^{N} w_{ij}\, x_j(n)\right)$$

monotonically decreases the energy function

$$E(\mathrm{x}) = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\, x_i x_j \tag{6}$$

until a stable equilibrium is reached.

Proof: Consider updating only neuron k at iteration n. The change in energy due to this update is:

$$\Delta E = E(\mathrm{x}(n+1)) - E(\mathrm{x}(n))$$

Only terms involving x_k change,

$$\Delta E = -\sum_{j=1}^{N} w_{kj}\, x_j(n)\,[x_k(n+1) - x_k(n)]$$

Since

$$x_k(n+1) = \operatorname{sgn}\left(\sum_{j=1}^{N} w_{kj}\, x_j(n)\right)$$

we have

$$\sum_{j=1}^{N} w_{kj}\, x_j(n)\, x_k(n+1) \geq \sum_{j=1}^{N} w_{kj}\, x_j(n)\, x_k(n)$$

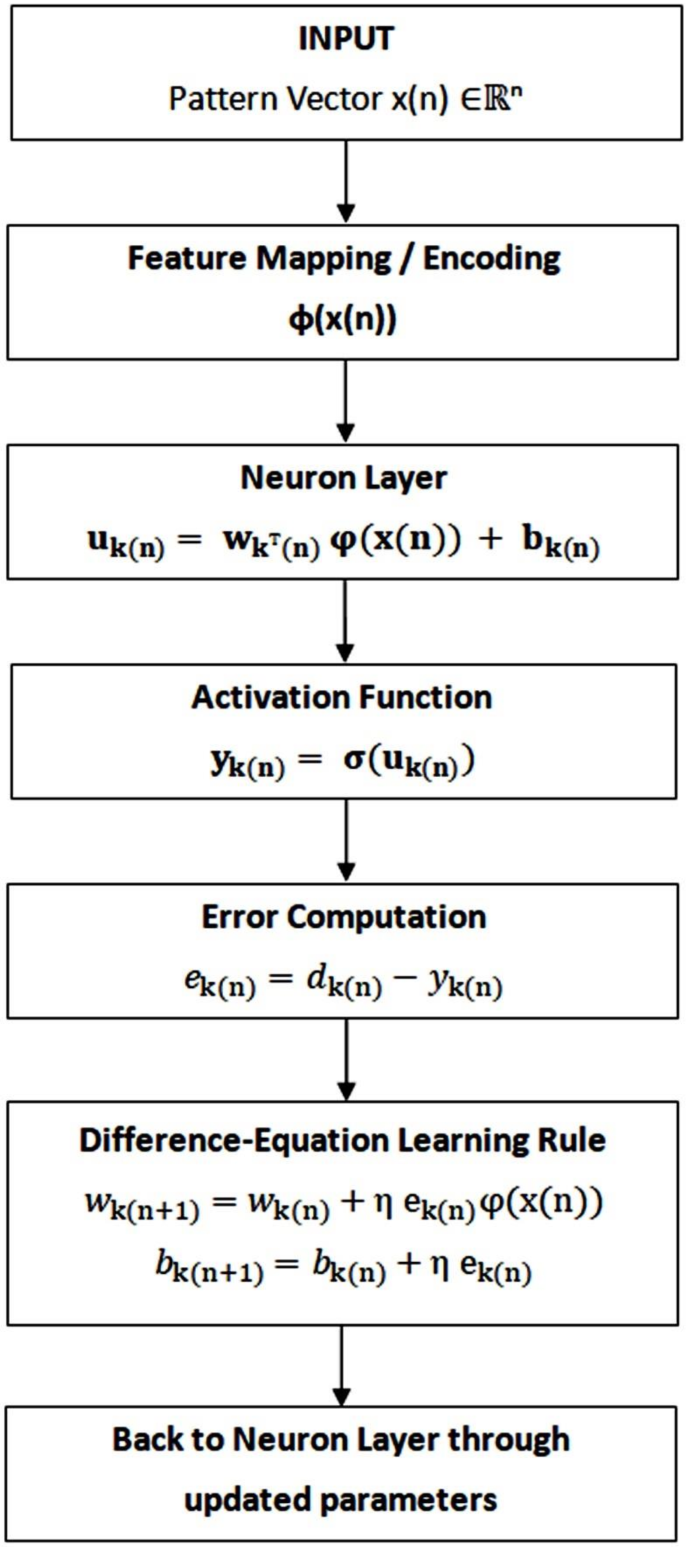

Figure 1.: Proposed error computation algorithm

which implies $\Delta E \leq 0$. Thus, the energy function never increases. Since the energy is bounded below, the system must converge to a stable state. The proposed error computational algorithm is discussed in figure 1.

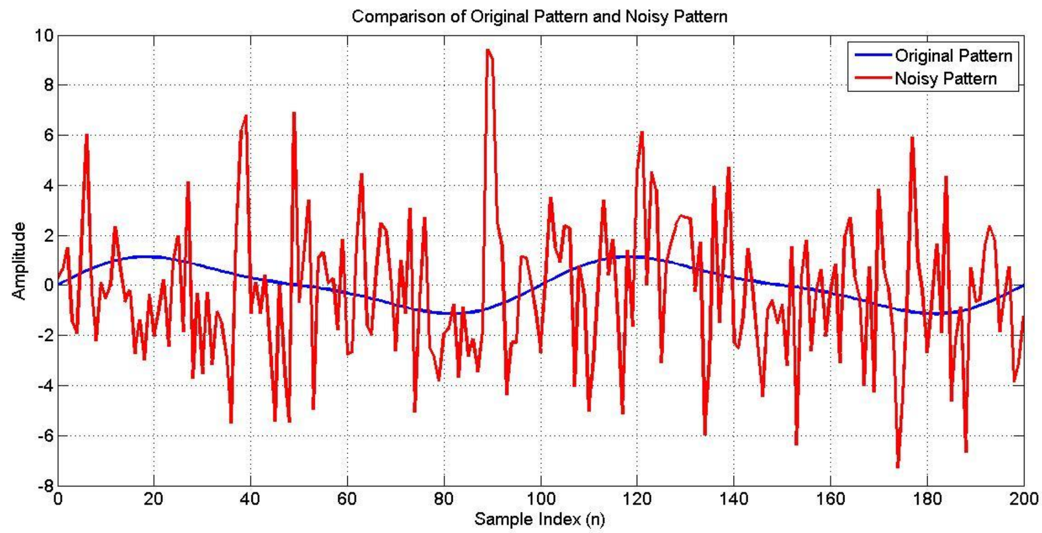

Figure 2.: Comparison of original pattern and noisy pattern when noise is high

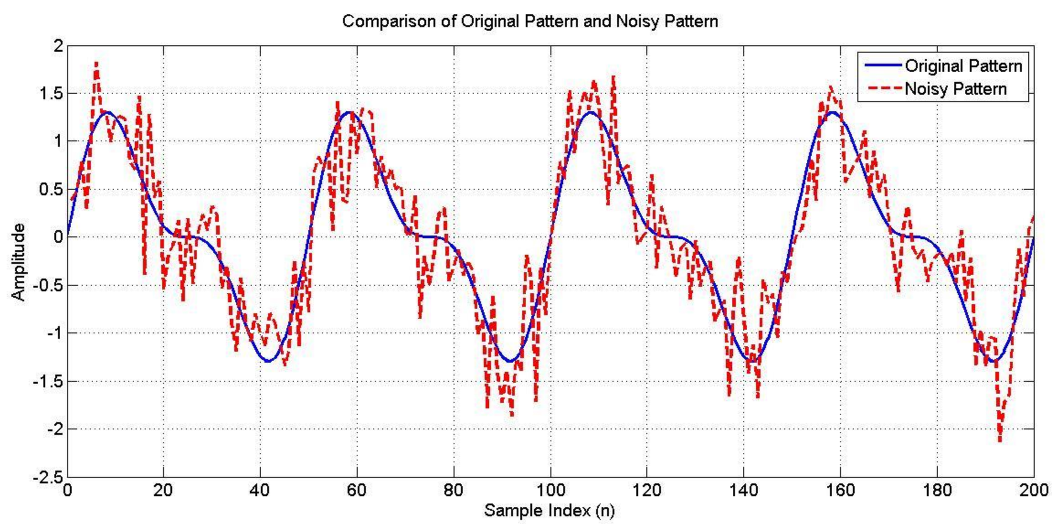

Figure 3.: Comparison of original pattern and noisy pattern when noise is moderate and tolerable.

Theorem 3.4: Pattern Convergence and Recognition Stability: Let x^* be a stored pattern such that

$$x_i^* = \phi\left(\sum_{j=1}^{N} w_{ij}\, x_j^*\right)$$

Then x^* is a stable equilibrium point of the brain-inspired neural system. Any initial pattern sufficiently close to x^* will converge to it.

Proof: At equilibrium, $x(n+1) = x(n) = x^*$. Linearizing the system around x^*, we have,

$$x(n+1) - x^* = J\,(x(n) - x^*)$$

where J is the Jacobian matrix of the update function. If the spectral radius satisfies $\rho(J) < 1$,

then, $\lim_{n\to\infty}(x(n) - x^*) = 0$. Hence, the system converges to x^*, ensuring stable pattern recognition. In pattern recognition, noise is modeled as a small perturbation in the input pattern. Let

$x \in \mathbb{R}^n$ be the true pattern

$x' = x + \eta$ be the observed (noisy) pattern

η be a disturbance vector

and noise is assumed to be bounded as [2, 10],

$$\| x - x' \| = \| \eta \| \leq \delta$$

where $\delta > 0$ is small. So, noise does not change the pattern arbitrarily, it only shifts slightly in the feature space. This is arrived and shown in figures 2 to 4. Assume that

$$f_i(x) - f_j(x) = \gamma > 0$$

This means x is correctly classified with a margin γ. For noisy input x', we have,

$$(x') - f_j(x') = \left[f_i(x) - f_j(x)\right] + [f_i(x') - f_i(x)] - [f_j(x') - f_j(x)]$$

Using Lipschitz bounds, $| f_i(x') - f_i(x) | \leq L\delta, | f_j(x') - f_j(x) | \leq L\delta$ and we get $f_i(x') - f_j(x') \geq \gamma - 2L\delta$. Finally the stable system i.e., comparison between the original pattern and noise reduced pattern is shown in figure 5.

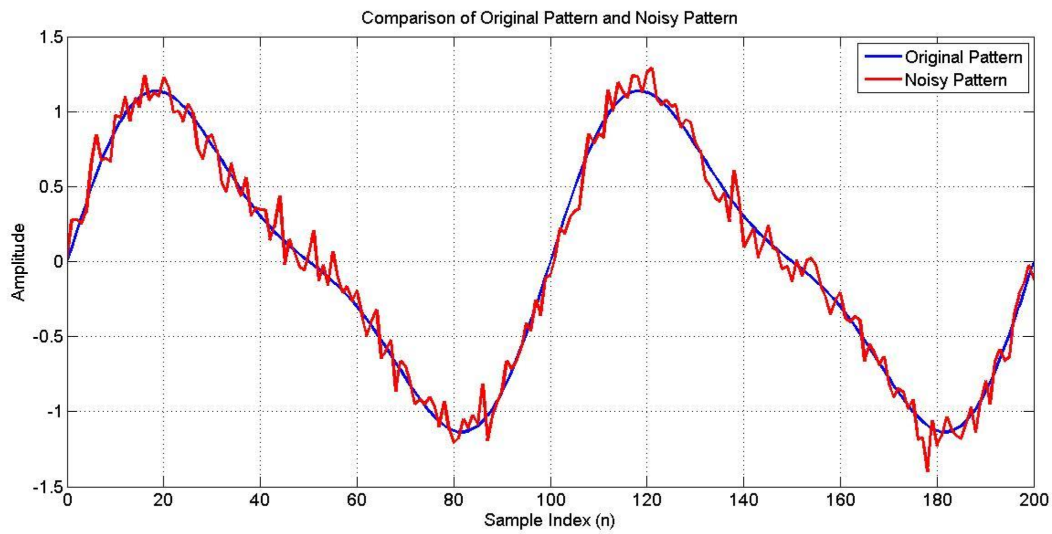

Figure 4.: Comparison of original pattern and noisy pattern when noise is low.

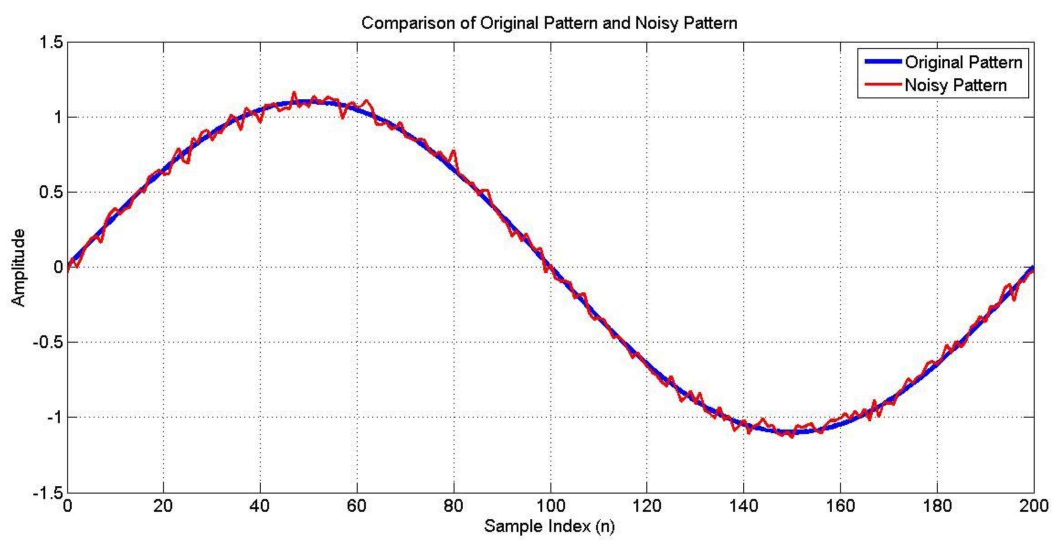

Figure 5.: Comparison of original pattern and noisy pattern when the system reaches the stability.

IV Conclusion

This study has demonstrated that biologically inspired pattern recognition principles provide a powerful and mathematically consistent framework for MIMO signal detection in complex communication environments. By interpreting received MIMO signals as high-dimensional patterns and modeling detection as an adaptive nonlinear classification problem, strong parallels were established between communication systems and biological signal processing mechanisms. Convolutional operations, stochastic difference equations, and adaptive learning dynamics effectively capture synaptic interactions, sensory encoding, and genetic regulation behaviors within a unified analytical structure. Theoretical analysis confirmed convergence, stability, and error reduction under realistic noise and interference conditions. These results indicate that biologically motivated detection strategies can achieve scalable, noise-robust, and adaptive performance in large MIMO systems. Overall, the proposed framework offers a promising direction for next-generation wireless receivers, bridging biological computation, pattern recognition, and advanced communication theory. Pattern recognition using neurons is fundamentally a dynamical process governed by difference equations. Single neurons perform linear classification, while networks of neurons enable associative memory, noise tolerance, and error correction. Theorems on separability, energy minimization, and stability provide strong mathematical justification for neuron-based pattern recognition systems and explain their biological plausibility.

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