Journal of Information Hiding and Multimedia Signal Processing ©2018 ISSN 2073-4212
Ubiquitous International Volume **9**, Number **2**, March **2018**

A Novel Blind Detection Algorithm Based On Double Sigmoid Hysteretic Chaotic Hopfield Neural Network

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Received May, 2017; revised December, 2017

Abstract. *A novel blind detection algorithm based on Double Sigmoid Hysteretic Chaotic Hopfield Neural Network(DS-HCHNN) is proposed. The algorithm adopted an adjustable hysteretic activation function, took advantage of the dynamic behavior of chaotic systems, and the simulation resulted convergence to the global minimum. Our simulation also showed that the algorithm was able to accelerate the convergence rate by introducing a new sigmoid structure with distance norm in the cost function. Compared to the Hysteretic Hopfield Neural Network(HHNN) blind detection algorithm and the traditional Hopfield Neural Network(HNN) blind detection algorithm, the proposed novel algorithm can not only converge to the global optimum, but also with a higher speed.*
Keywords: Chaotic Hopfield Neural Network; hysteresis activation function; Double Sigmoid; Blind detection

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1. **Introduction.** Blind detection technology is a method that detects the signal sequence to the transmitter through the sequence from the receiver without training signal sequences. While the blind detection method based on Higher-Order Statistics(HOS) depends on large amount of data and the method based on Short-Order Statistics(SOS) is not compatible with channels containing common zero, the method based on Hopfield Neural Network (HNN) is widely used because it enjoys the advantages of low computational complexity, short data sequence requirement and compatibility for channels containing the common zero [1-6]. However, HNN may be subject to local minima convergence due to its gradient descent dynamics [7]. Reference [8] showed a method that introduced a hysteresis activation function into HNN, constructed a new network model with proven stability of the network, and has been applied to solve the N-queen problem successfully. A novel blind detection algorithm was proposed [9] based on Hysteretic Hopfield Neural Network (HHNN), and the hysteresis activation modestly improved the performance of the blind detection algorithm. Transient Chaotic Neural Network(TCNN) [10] can avoid the local optimum issue, but has a negative self-coupling. Double Sigmoid

Transient Chaotic Neural Network(DS-TCNN) [11] is proposed to solve the slow convergence issue of the energy function of TCNN. Economic load dispatch of power systems [12] and OFDMA System [13] have achieved very good performance after introducing hysteresis chaotic neural network and overcome the premature saturation issues caused by the traditional sigmoid function in chaotic neural network and HNN.

Here a novel blind detection algorithm based on DS-HCHNN is proposed in this paper that combines the advantages of TCNN and hysteresis activation function, and solves the slow convergence issue of energy function. In order to adapt to blind detection, we constructed DS-HCHNN, designed a novel hysteretic activation function, and proved the stability of the network. The simulation results illustrated that this novel idea has significantly improved the performance of blind detection algorithm.

2. **Double Sigmoid Hysteretic Chaotic Hopfield Neural Network.** The block diagram of DS-HCHNN proposed in this paper is showed in figure1.

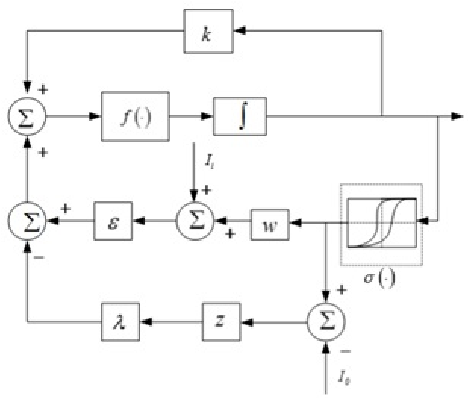

FIGURE 1. The block diagram of DS-HCHNN.

The dynamic equation of the proposed DS-HCHNN is written as follows:

$$y_i(t+1) = f(ky_i(t) + \varepsilon[\sum_{j=1}^{n} w_{ij}x_j(t) + I_i] - z_i(t)(x_i(t) - I_0)) \tag{1}$$

$$x_i(t) = \sigma(y_i(t)) \tag{2}$$

$$z_i(t+1) = (1-\beta)z_i(t) \tag{3}$$

$$f(t) = sign(t) \tag{4}$$

where, (1) is the dynamic equation of the DS-HCHNN; (2) is the activation function, (3) is the annealing function, and (4) is the sigmoid function.
where the variables are

w_{ij} connection weight of the neuron ;
I_i neuron bias;
I_0 a constant;
ε attenuation factor for the neuron;
β the simulated annealing parameter;
$z_i(t)$ self-feedback connection.

Different from other traditional activation functions, this paper designs a new hysteretic activation function as follows:

$$x_i(t) = \sigma(y_i(t)) = \begin{cases} \tanh(a \cdot y_i(t) + b) & \Delta y_i(t) \geq 0 \\ \tanh(a \cdot y_i(t) - b) & else \end{cases} \tag{5}$$

where, a can adjust the steepness of function, b is the mapping factor, controlling the mapping interval. The first advantage of the new hysteresis activation function was that hysteresis activation function parameters are very flexible. Fig. 2 is activation function graph with fixed a and different b. From Fig. 2, we can see that the function changes significantly over subtle changes of parameter a, and therefore, it is important to select appropriate parameters to improve the performance of the algorithm. The parameter selection process will be described in detail in the next chapter. The second advantage is that the output of the neuron not only depends on its input, but the input of the neuron before and after the two input changes. Its better to resolve the disadvantages that the neural network is vulnerable to input values.

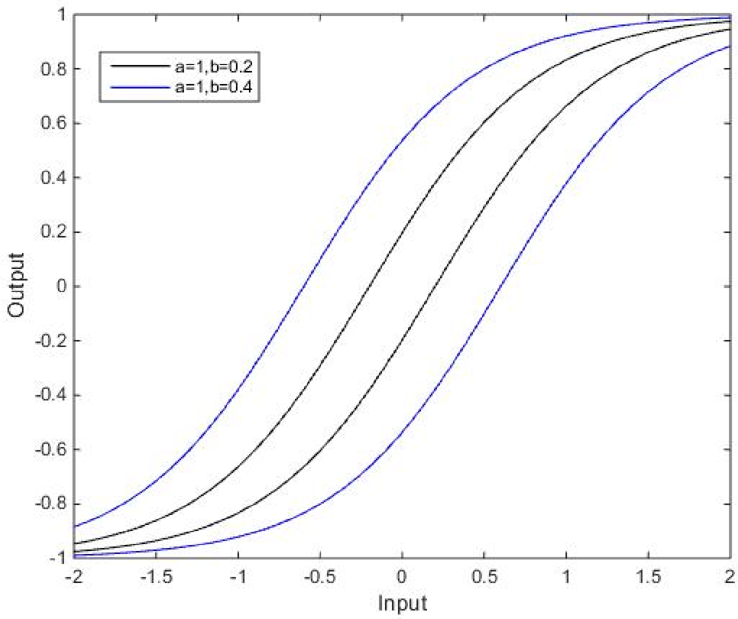

Figure 2. Hysteretic activation function.

The stability of the DS-HCHNN can be demonstrated as follow:

$$\begin{aligned} E &= E_{Hopfield} + E_{add} \\ &= -\frac{\alpha}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} x_i w_{ij} x_j - k\sum_{i=1}^{N}\int_0^{x_i(t)} {\sigma_i}^{-1}(\tau)d\tau - \alpha\sum_{i=1}^{N} I_i x_i + \frac{\lambda}{2}\sum_{i=1}^{N} z_i(t) x_i^2(t) \end{aligned} \tag{6}$$

$$\frac{dE}{dt} = -\{k' y_i(t) + \alpha(\sum_{j=1}^{N} w_{ij} x_j + I_i) - \lambda z_i(t)\}\frac{dx_i(t)}{dt} - \frac{\lambda\beta'}{2}\sum_{i=1}^{N} x_i^2(t) \tag{7}$$

According to Euler approximate, Eq.(1) and Eq.(3) can be expressed as:

$$\frac{dy_i\,(t)}{dt} = f(k' y_i(t) + \varepsilon'[\sum_{j=1}^{n} w_{ij} x_{\mathrm{j}}(t) + I_i] - \lambda z_i(t)(x_i(t) - I_0)) \tag{8}$$

$$\frac{dz_i\left(t\right)}{dt} = -\beta \quad (\beta > 0) \tag{9}$$

Continue to simplify Eq. (7) by substituting Eq. (8) and Eq.(9):

$$\frac{dE}{dt} = -\sum_{i=1}^{N} \frac{d\sigma(y_i(t))}{dy_i(t)} \cdot \frac{dy_i(t)}{dt} \cdot f^{-1}(\frac{dy_i(t)}{dt}) - \frac{\lambda\beta'}{2} \sum_{i=1}^{N} x_i^2(t) \tag{10}$$

Because sigmoid funtion $f(\cdot)$, and according to the nature of $\sigma(\cdot)$ we can know $\frac{d\sigma(y_i(t))}{dy_i(t)} > 0$, $\frac{dy_i(t)}{dt} > 0$, $f^{-1}(\cdot) > 0$, and $\frac{\lambda\beta'}{2}\sum_{i=1}^{N} x_i^2(t) > 0$, $\frac{\mathrm{d}E}{\mathrm{d}t} > 0$. Based on Lyapounov stability theorem, the network energy function is stable because network energy value decreased during the iteration operation.

3. **Weight Matrix Configuration.** Ignoring the noise, the reception equation for the discrete time channel is defined as follows:

$$X_N = S\Gamma^T \tag{11}$$

where, X_N is receiving data matrix, N is length of sending signal matrix, S is sending signal matrix, Γ is block Toeplitz matrix formed by the channel impulse response, $(\cdot)^T$ represents the matrix transpose.

Eq. (11) shows that, while Γ is column full rank matrix, there must be $Q = u_c u_c^H$, with $Qs_N(k-d) = 0$. u_c is Unitary array of the SVD. $x_N = [u,u_c] \cdot \begin{bmatrix} d \\ 0 \end{bmatrix} \cdot v^T$, $u_c \in C^{N\times(N-(L+M+1))}$. Thus, we can construct cost function and the optimization problem as follows:

$$J_0 = s_N^H(k-d)Qs_N(k-d) = s^H Qs \tag{12}$$

$$\hat{s} = \mathop{\arg\min}_{\hat{s}\in\{\pm1\}^N} \{J_0\} \tag{13}$$

To implement the blind detection of signal Eq. (6) and Eq. (7) using the DS-HCHNN, the minimum value of the energy function should correspond to the minimum point of the blind performance function. Approximately $s_i(t) = x_i(t)$ when the network is stable. By comparing the first term of the energy function in Eq. (6), we can adopt the DS-HCHNN weight matrix $W = I_N - Q$, where I_N is N*N unit matrix and $Q = u_c u_c^H$. This design allowed the match of the minimal data points between energy function E(t) and DS-HCHNN in Eq. (2), and thus the signal blind detection can be better realized by DS-HCHNN.

4. **Simulation Experiment.** Simulation environment: the experiment uses additive white Gaussian noise, channel function $h(t) = \sum_{j=1}^{2} (w_j(h(\alpha, t-\tau_j)))$. Where, $h(\alpha, t-\tau_j)$ is the roll-off factor, $\alpha = 0.1$ is the delay factor, τ_j is a randomly generated raised cosine impulse response, w_j is a random weight coefficient. The sending signal is Binary Phase Shift Keying and Binary Phase Shift Keying(BPSK) signal, q=3 is oversampling factor, signal propagation multipath number is 2. Each simulation result was from running Monte Carlo experiments 100 times. The bit error rate(BER) of zero in simulation was reset to 10^{-5} in plotting [14].

4.1. **Experiment 1:** We fix signal-to-noise ratio (SNR) = 20dB, choose the synthesis channel with fixed weight and time delay containing no zero. To choose the optimal set of parameter values for the hysteretic activation function, we first obtained the optimal range of $a \in (0, 2)$, $b \in (0, 1)$ from results of running simulation many times. Next, we took the performance function J=SQS as the indicator, varying a and b at the same time in simulation, and resulted The three-dimensional map of these parameters shown in Fig. 3.

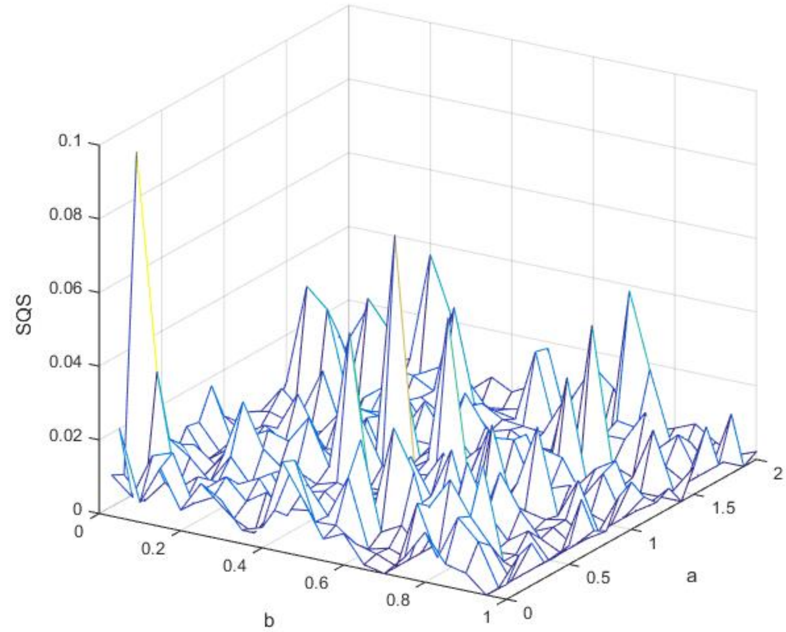

FIGURE 3. The impact of the parameters a and b to the cost function J.

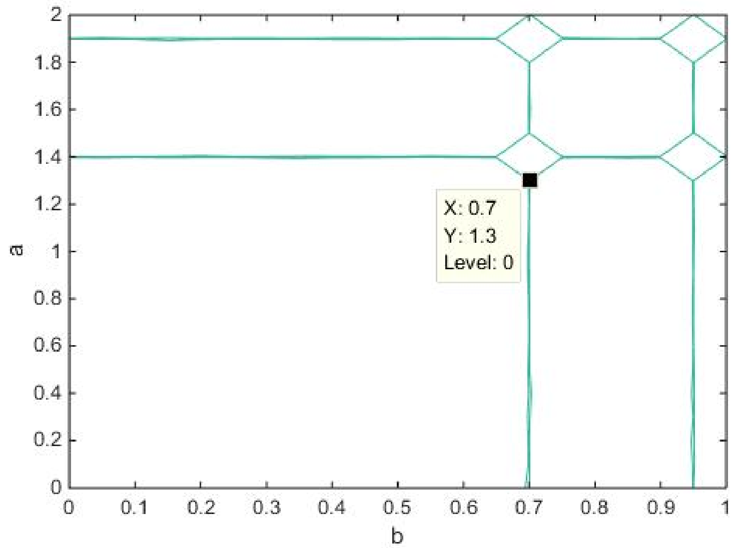

FIGURE 4. the sectional view of J=0.

As shown in Fig. 3, we can see that different values of a,b result in different J. According to the principle of blind detection, the global minimum value of the cost function J = SQS is the stable equilibrium point of the HNN. Fig. 4 shows the sectional view of J = 0, which all the value of a and b corresponding to the cost function J=0. Blind detection network can achieve good performance when we randomly selected three groups of a,b values from Fig. 4. For the following experiment we choose a= 1.3, b = 0.7.

4.2. **Experiment 2:** we fix input signal sequence N = 100, and choose random synthesis channel with varying weight and varying time delay. The BER of DS-HCHNN, HNN [7], HHNN [9], and TCNN [10] are compared in Fig. 5.

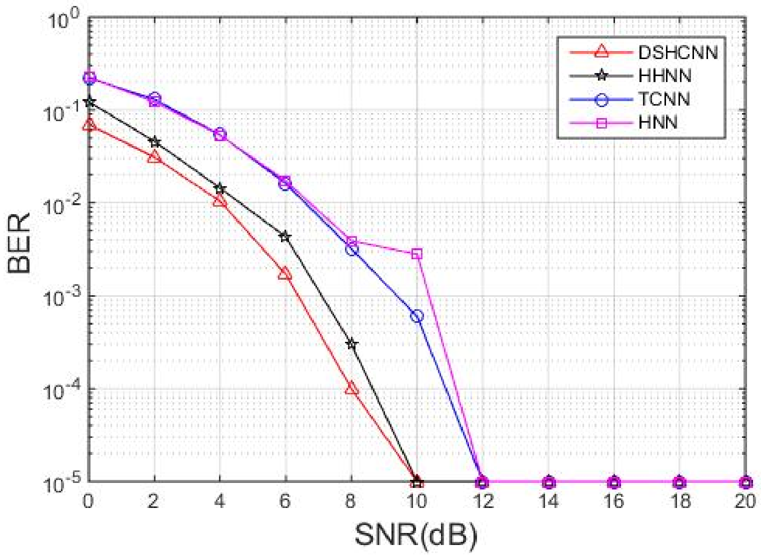

FIGURE 5. BER under random synthesis channel.

As shown in the Fig. 4, DS-HCHNN and HHNN decrease to 0 when SNR =10dB, and TCNN and HNN drop to 0 at SNR =12dB. Under the same conditions DS-HCHNN blind algorithm has the lowest BER, compared to the other three algorithms.

4.3. **Experiment 3:** The relationship between BER and the length of the transmitted data is studied by using the synchronization update mode with fixed weight, fixed time delay synthesis channel containing no zero. We vary the data length of DS-HCHNN blind detection algorithm from 200, 100 to 50, the data length of HNNN [9] from 300, 200 to 100.

As showed in Fig. 6 and Fig. 7, in the synchronous update mode, BER of the DS-HCHNN blind detection algorithm increased much less with the reduction in the length of sending signal data compared to HHNN. In addition, to reach similar BER performance, DS-HCHNN required much shorter sending data than HHNN, for example, when SNR=8dB, BER of DS-HCHNN at data length N=50 is close to HHNN at data length N=300.

4.4. **Experiment 4:** Comparison of convergence speed. We fix SNR=16dB, choosing random synthesis channel with varying weight and varying time delay, comparing convergence speed among the HNN [7], HHNN [9], TCNN [10], DS-TCNN [11], and DS-HCHNN. In this simulation we introduce a new performance indicator, distance norm which is the distance of the state vector and the equilibrium point index. The experimental results are shown in Fig. 8.

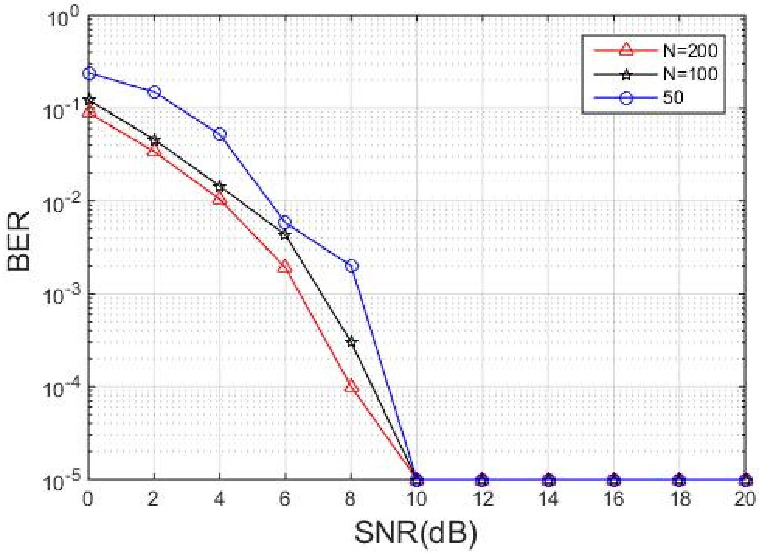

FIGURE 6. BER of DSHCHNN under different data.

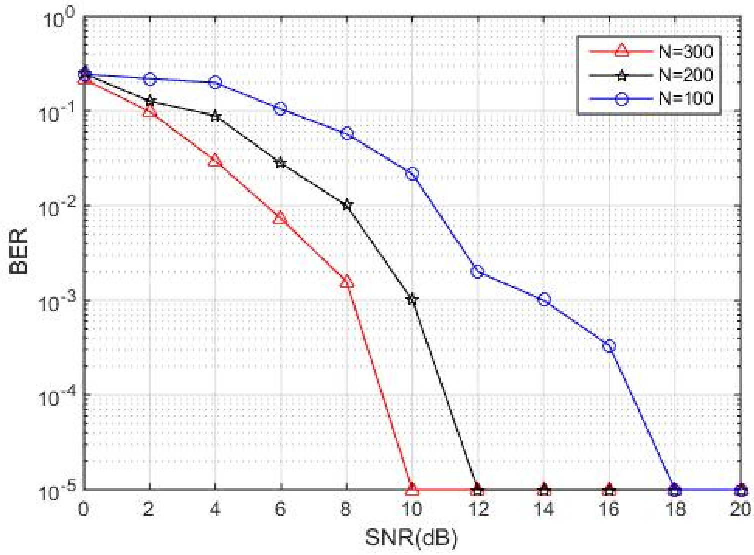

FIGURE 7. BER of HHNN under different data.

The distance norm refers to the modulus between the two vectors. The norm of the vector is defined as: a function $\| x \|$ that satisfies the nonnegative, $\| x \| \geq 0$, homogeneous $\| cx \| = |c| \| x \|$ and Triangular inequality, $\| x + y \| \leq \| x \| + \| y \|$. The distance norm of the this paper choose the L_2 norm, which is the square of the sum of squares of the elements of the vector.

Fig. 8 shows that DS-HCHNN converges faster than the other four algorithms. From the inlet diagram, the convergence speed of TCNN blind algorithm is slower after the introduction of chaos on the basis of HNN, and DS-TCNN can get faster than HNN and TCNN, which further explain the effectiveness of double sigmoid structure.

5. **Conclusion and Future Work.** A novel DS-HCHNN blind detection algorithm has been proposed in this paper that greatly improved the performance of the blind detection

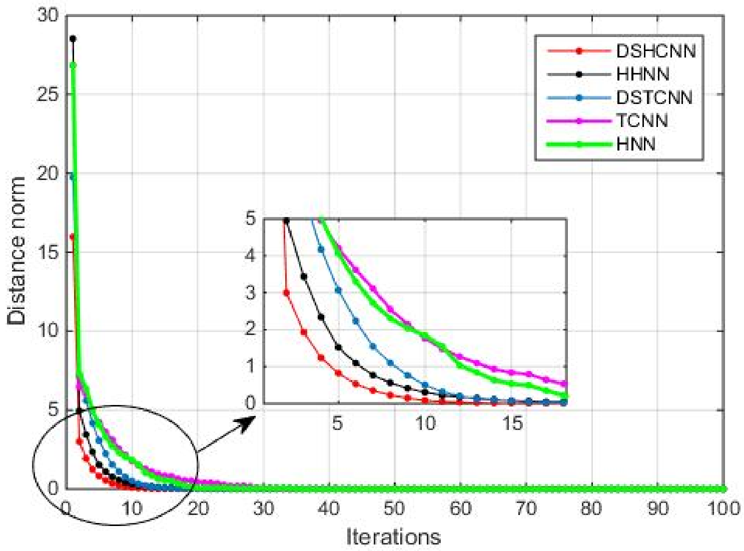

FIGURE 8. Distance norm of different algorithms.

algorithm. It is characterized by the combined advantages of hysteresis, chaos and double sigmoid [15] structure. Utilizing the abundant ergodicity and pseudorandomness of chaotic neural network, the algorithm is able to converge to the global optimum instead of local optimum. The novel hysteresis activation possessing the ability of associative memory and storage can improve the anti-interference ability of the algorithm. The double sigmoid structure greatly improve the convergence rate of the algorithm. From the experimental results, only shorter sending signal can the novel algorithm reap low BER and fast convergence rate. In short, DS-HCHNN greatly optimizes the performance of the blind detection algorithm.

Future work includes research on potentially better ways to improve the convergence rate of the algorithm. In addition, simulated annealing will be further improved because at certain initial conditions the network may not reach a steady state that is required by chaos simulated annealing. Finally, we will study how to build a hardware platform based on hysteretic chaotic neural network.

Acknowledgment. The authors would like to thank the support of this work by Grants from the National Natural Science Foundation of China (NSFC) (No.61302155,No.61274080) , the introduction of talent Project of Nanjing University of Posts and Telecommunications(No.NY2l4052) and Jiangsu Government Scholarship for Overseas Studies.

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