Randomness of memory patterns plays important roles in sensitive response to memory pattern fragments

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Abstract: In the present paper, we investigate roles of the randomness of memory patterns in the sensitive response of the chaotic associative memory dynamics to memory pattern fragments in the chaotic neural network model referred to as CNN hereafter. In order to realize a memory search for hierarchical memory patterns, we overcome the problem how to construct the hierarchical memory patterns, whose basin volumes and visiting measures are sufficiently large. Therefore, we investigate (i) how to construct the memory patterns which gives sufficiently large basin volumes of theirs in a recurrent neural network model referred to as RNN hereafter, and (ii) the sensitivity of the chaotic associative memory dynamics in CNN to memory pattern fragments, focusing on the randomness in the memory patterns. From computer experiments, the basin volumes of the memory patterns become much larger as the randomness increases. In addition, the sensitive and robust response to the memory pattern fragments is achieved as the randomness becomes larger. Thus, ensuring sufficient large basin volumes and visiting measures with the same frequency, and the quite sensitive and robust response to the memory pattern fragments, the randomness in memory patterns is practical, which introduces the small overlap among each inter-cycle pattern.

Key Words: chaotic neural network, chaotic associative memory dynamics, sensitive and robust response, memory pattern fragments, randomness

1. Introduction
The roles of chaos in information processing in human brain, learning, memory search, recognition and so on, have been investigated by pioneer workers [1–5]. The results are quite attractive and important in understanding mechanisms of information processing in human brain. Inspired by the works, we started to investigate roles of chaos in CNN.

We have investigated the sensitive and robust response to memory pattern fragments of the chaotic
associative memory dynamics in CNN related with a memory search function [6–10]. We have shown that once a certain memory pattern fragment is applied to CNN, an orbit of the chaotic associative memory dynamics quickly moves to the vicinity of the corresponding memory pattern including the fragment within several iteration steps. In addition, as the dynamical complexity of the chaotic associative memory dynamics increases, the delocalizing effects in visiting attractor basins become larger. In fact, the orbit in an intra-cycle extends to an inter-cycle as the dynamical complexity increases. The results suggest that we could realize an instantaneous memory search with hierarchical memory patterns by controlling the dynamical complexity and applying a memory pattern fragment as a key input of the search.

However, we found that for the memory patterns with certain structures, in general, their basin volumes and furthermore visiting measures of the attractor basins of theirs become quite small. For small basin volumes and visiting measures, it would be difficult to access the vicinity of the corresponding memory pattern by applying a memory pattern fragment into the chaotic associative memory dynamics. Thus, in order to realize an instantaneous memory search with hierarchical memory patterns, it is practical to ensure sufficient large basin volumes and visiting measures with the same frequency.

Therefore, the purposes of the present paper are (i) to investigate how to construct the memory patterns which gives sufficiently large basin volumes of theirs in RNN, and (ii) to study the sensitivity of the chaotic associative memory dynamics in CNN to memory pattern fragments, focusing on the randomness in the memory patterns. We apply 11 kinds of the memory patterns with changing the ratio of the randomness. Then, we evaluate basin volumes of each memory patterns in RNN and visiting measures in CNN with changing the randomness. Finally, we investigate the sensitivity and robustness of the chaotic associative memory dynamics in CNN to memory pattern fragments.

In section 2, we present basic equations of RNN and CNN, and information dimension which quantifies the dynamical complexity of associative memory dynamics. In section 3, we give results of basin volumes in RNN with changing the randomness. In section 4, we give results of visiting measures in CNN, and the sensitivity and robustness to memory pattern fragments with changing the randomness. Section 5 and section 6 are devoted to discussions and conclusion.

2. Basic equations

2.1 RNN

We employ RNN to evaluate basin volumes of the memory patterns. Therefore, let us explain RNN briefly. The updating rule of RNN is represented as follows,

\[ u_i(t + 1) = \sum_{j=1}^{N} w_{ij} z_j(t), \]  

(1)

where \( u_i(t) \) represents an internal state of the \( i \)th neuron at a time step \( t \), \( w_{ij} \) denotes a synaptic connection from the \( j \)th neuron to the \( i \)th one, \( z_j(t) \) describes an output of the \( j \)th one, and \( N \) corresponds to the total number of neurons. The output of the \( i \)th neuron at a time step \( t \) in RNN is given by,

\[ z_i(t) = f(u_i(t); \beta), \]  

(2)

where the function \( f(x; \beta) \) describes an output function with a steepness parameter of \( \beta \) at \( x = 0 \). In the present paper, as the function \( f(x; \beta) \), we employ hyperbolic tangent function with a parameter of \( \beta \) as follows,

\[ f(x; \beta) = \tanh(\beta x). \]  

(3)

2.2 Adachi & Aihara CNN

In the present paper, we employ Adachi & Aihara CNN to introduce chaotic associative memory dynamics [11]. The internal state of the \( i \)th neuron at a time step \( t \) consists of two kinds of terms, the associative effect and the refractoriness effect, as follows,

\[ u_i(t) = \eta_i(t) + \zeta_i(t), \]  

(4)
where \( \eta_i(t) \) denotes the associative effect and \( \zeta_i(t) \) describes the refractoriness effect.

The associative effect of the internal state of the \( i \)th neuron is represented by,

\[
\eta_i(t + 1) = k_\eta \eta_i(t) + \sum_{j=1}^{N} w_{ij} f(u_j(t); \varepsilon_\eta)
\]

where \( k_\eta \) is a decay parameter, the output function \( f(\cdot) \) is given by Eq. (3) and \( \varepsilon_\eta \) is the steepness parameter of the output function for the refractoriness effect.

The refractoriness effect of the internal state of the \( i \)th neuron is written by,

\[
\zeta_i(t + 1) = k_\zeta \zeta_i(t) - \alpha f(u_i(t); \varepsilon_\zeta) + a_i,
\]

where \( k_\zeta \) represents a decay parameter, \( \alpha \) is a relative refractory scaling parameter, \( \varepsilon_\zeta \) is the steepness parameter for the refractoriness effect, and \( a_i \) is a constant bias input. The existence of the relative refractory term of \( -\alpha f(u_i(t); \varepsilon_\zeta) \) and the constant bias input of \( a_i \) introduce chaotic associative memory dynamics in the system.

Note that since there are two type of outputs, one for the associative effect and the other for the refractoriness effect, the former is employed as the whole network’s output.

### 2.3 Orthogonal learning method

In the present paper, we employ an orthogonal learning method to determine synaptic connections. In general, basin volumes of the memory patterns become larger with the orthogonal learning method. In addition, we apply memory patterns with multi cycles since their basin volumes become larger. Therefore, the orthogonal learning method for memory patterns with multi cycles is written as follows:

\[
w_{ij} = P \sum_{a=1}^{P} \sum_{\mu=1}^{L} v^{(a)(\mu+1)}(i) (v^{(a)(\mu)})^\dagger,
\]

where \( v^{(a)(\mu)} \) denotes the \( \mu \)th memory pattern vector among the \( a \)th cycle, \( (v^{(a)(\mu)})^\dagger \) is a conjugate vector of \( v^{(a)(\mu)} \), \( P \) represents the total number of cycles, and \( L \) represents the total number of patterns in each cycle. It should be noted that \( v_i^{(a)(L+1)} \) is regarded as \( v_i^{(a)(1)} \).

The conjugate vector is defined as follows:

\[
(v^{(a)(\mu)})^\dagger = \sum_{b=1}^{P} \sum_{\nu=1}^{L} (O^{-1})^{(a)(\mu)(b)(\nu)} v^{(b)(\nu)}
\]

where \( O^{-1} \) is an inverse matrix of the overlap matrix calculated by,

\[
O^{(a)(\mu)(b)(\nu)} = \sum_{k=1}^{N} v_k^{(a)(\mu)} v_k^{(b)(\nu)}
\]

Note that applying Eq. (7), \( P \) kinds of limit cycle memory patterns with a period of \( L \) are embedded in RNN and Adachi & Aihara CNN.

### 2.4 Information dimension and visiting measure

In the present paper, we apply information dimension which quantifies the dynamical complexity of the chaotic associative memory dynamics. The information dimension is evaluated by,

\[
d = - \sum_{a=1}^{P+1} \text{Prob}(a) \log_{P+1} \text{Prob}(a),
\]

where \( \text{Prob}(a) \) represents a visiting measure of the \( a \)th cycle pattern and the \((P + 1)\)th pattern corresponds to the spurious pattern. In order to normalize the maximal information dimension to be 1, the base of a logarithm is set to be \( P + 1 \).
Fig. 1. Eleven kinds of cycle patterns with changing the ratio of the randomness. (a) Original memory patterns without randomness. (b) Memory patterns including 10% randomness. (c) 20%. (d) 30%. (e) 40%. (f) 50%. (g) 60%. (h) 70%. (i) 80%. (j) 90%. (k) 100%. The black pixels represent 1 and the white ones -1. “A”, “B” and “C” represent cycle indexes, and “1”, “2”, ···, “7” denote pattern indexes in each cycle.

The visiting measure is evaluated by counting which basins of memory patterns an orbit of the chaotic associative memory dynamics in Adachi & Aihara CNN passes at each time step. In order to determine which basins the orbit passes, we set outputs of Adachi & Aihara CNN at each time step among its updating as an initial configuration of RNN, and we check which memory patterns RNN converges into within 100 steps. In the comparison of the RNN’s outputs with the memory patterns, we regard the RNN’s output as 1 if \( z_i(t) \geq 0 \), and as \(-1\) if \( z_i(t) < 0 \). The same transformation of the RNN’s outputs is applied in the calculation of the basin volume. In the evaluation, we divide the converging states into two types:

1. Cycle memory patterns: The system converges into one of \( P \) cycle patterns. Thus, each cycle pattern is indexed from 1 to \( P \). In addition, the inverse pattern is regarded as corresponding the memory pattern.

2. Spurious pattern: The system converges into spurious patterns or non-convergent state. In this case, we index with \( P + 1 \).

We evaluate the visiting measure with use of \( T \) different points of the orbit of the chaotic associative memory dynamics from \( T_0 + 1 \) to \( T_0 + T \) steps.

3. Effects of randomness in memory patterns for basin volume

3.1 Purpose and method

One of purposes in the present paper is to investigate how to construct the memory patterns which gives sufficiently large basin volumes of theirs in RNN. In other word, we study whether the randomness in memory patterns introduces sufficient large basin volumes or not. We apply 11 kinds of cycle patterns with changing the ratio of the randomness as shown in Fig. 1. Memory patterns are composed of \( P = 3 \) cycles, each cycle contains \( L = 7 \) patterns, and each pattern consists of \( 30 \times 20 \) pixels of \( \pm 1 \), implying \( N = 600 \). “A”, “B” and “C” represent cycle indexes, and “1”, “2”, ···, “7” denote pattern indexes in each cycle. The patterns in each cycle contain a common region of \( 10 \times 20 (= 200) \) pixels even though the patterns include randomness, but the patterns among different cycles do not
have. Thus, for patterns including randomness, the common 200 pixels take the same randomness. In our memory patterns, therefore, the overlap among intra-cycle patterns is larger than inter-cycle patterns as shown in Fig. 2. Especially, for the patterns with the randomness of larger than 50%, the overlap among intra-cycle patterns is much larger than all the inter-cycle patterns.

The basin volume is calculated by starting from 20,000 different random initial patterns of RNN. At each time step of the updating of RNN, we check whether an output of RNN corresponds to one of memory patterns or not. If the output coincides with a certain one, we regrad that the system is in the cycle where the memory pattern belongs. Note that we regard the inverse pattern as the corresponding memory pattern. On the other hand, when the system does not coincide until 40 time steps, we stop the calculation and we regard that either the system could not converge or the system is among a certain spurious cycle pattern, denoting as a spurious pattern. Through the computer experiments, we employ the same parameter value of $\beta = 100$.

3.2 Basin volume

The results of basin volume are given in Fig. 3, where the basin volume of each cycle pattern and the total basin volume of all the cycle patterns are depicted. For the patterns with the randomness of smaller than 40%, the basin volume of each cycle pattern is quite smaller than the spurious pattern. On the other hands, for the patterns with the randomness of larger than 50%, the basin volume of each cycle pattern is larger than the spurious pattern. In addition, the total basin volume of all the cycle patterns is quite larger than the spurious pattern. Therefore, we expect that the orbit of the chaotic associative memory dynamics would wander among the basins of the memory patterns with

![Fig. 2. Overlap between the A1 pattern and the others.](image)

![Fig. 3. Basin volumes. (a) Basin volume of each cycle pattern and the spurious pattern. (b) Total basin volume of all the cycle patterns and the spurious pattern. “A”, “B” and “C” indicate cycle indexes, and “D” represents the spurious pattern.](image)
higher frequency than the spurious pattern.

Now, we investigate why basin volumes of the memory patterns with higher randomness become larger. We focus on the overlap among intra-cycle or inter-cycle patterns. As shown in Fig. 2, the overlap among intra-cycle patterns is much larger than all the inter-cycle patterns for the patterns with the randomness of larger than 50%. As the overlap among inter-cycle patterns becomes smaller, the basin volume of the spurious pattern becomes smaller. Thus, ensuring basin volumes of the cycle patterns large, it is practical that the overlap among inter-cycle patterns becomes small.

4. Visiting measures and sensitive response

4.1 Evaluation results of visiting measures and information dimension

In evaluation of visiting measures, we employ the A1 pattern as an initial configuration of Adachi & Aihara CNN. We set $T_0 = 15,000$ and $T = 5,000$. We calculate visiting measures with changing the relative refractory scaling parameter of $\alpha$.

The results of the visiting measure and information dimension are given in Figs. 4 and 5, respectively. For $\alpha$ of almost smaller than 0.2, the visiting measure of the cycle A takes 1 and the others take 0, regardless of the degree of the randomness. In addition, the information dimension takes 0. In the case of the patterns with 100% randomness, for $0 \leq \alpha \leq 0.18$, the visiting measure of the cycle A takes 1 and the others take 0, and then the information dimension takes 0. The fact suggests that the system is in either limit cycle of the cycle pattern A or intra-cycle chaos among it because we start the calculation from the A1 pattern.

Subsequently, $\alpha > 0.18$, the behavior is different between 40% and 50% randomness. For the patterns with the randomness of smaller than 40%, the visiting measure of the spurious pattern becomes much larger than all the cycle patterns. For the patterns with the randomness of larger than 50%, the visiting measure of the cycle A decreases, on the other hand, the visiting measure of the spurious pattern increases. It should be noted that the visiting measure of the cycle A is much larger than the spurious pattern except for the case of 90% randomness. The measure of the other cycle patterns becomes non zero value but takes quite small. Therefore, the information dimension takes non zero value. In the case of the patterns with 100% randomness, for $0.19 \leq \alpha \leq 0.75$, the visiting measure of the cycle A decreases and the visiting measure of the spurious pattern increases. The information dimension suddenly takes non zero value of 0.38 at $\alpha = 0.19$.

As $\alpha$ becomes larger and larger, for the patterns with the randomness of larger than 50%, the visiting measure of each cycle pattern becomes almost the same value. In addition, the visiting measure of each cycle pattern is larger than the spurious pattern. In this region of $\alpha$, the information dimension takes the largest value, suggesting that dynamics is complex. In the case of the patterns with 100% randomness, for $0.76 \leq \alpha \leq 0.96$, the visiting measure of each cycle pattern becomes almost the same, and the measures is larger than the spurious pattern. The information dimension takes almost 0.99.

The results told us that the large randomness is important to ensure larger visiting measure of each cycle pattern with the same frequency than the spurious pattern. For the patterns with the randomness of larger than 50%, the behavior of the visiting measures and information dimension changes stepwisely including some fluctuations. It suggests that dynamics changes smoothly, limit cycle, intra-cycle chaos, inter-cycle chaos, and highly developed chaos.

4.2 Sensitive response

Sensitivity of the chaotic associative memory dynamics to memory pattern fragments is calculated by following procedures.

1. Update Adachi & Aihara CNN until $T_0$ steps in order to discard transient states.

2. After $T_0$ steps, we apply one of memory pattern fragments into the system. Thus, the updating rule of Eq. (4) is changed as follows:

$$u_i(t + 1)' = \eta_i(t + 1) + \zeta_i(t + 1) + \rho_\sigma I_i,$$

(11)
Fig. 4. Visiting measures. (a) 0% randomness. (b) 10% randomness. (c) 20% randomness. (d) 30% randomness. (e) 40% randomness. (f) 50% randomness. (g) 60% randomness. (h) 70% randomness. (i) 80% randomness. (j) 90% randomness. (k) 100% randomness. Visiting measures are calculated by starting from the A1 memory pattern as initial configuration of Adachi & Aihara CNN.

where $I_i$ represents a memory pattern fragment, $\rho$ denotes the strength of the fragment and $\sigma_i$ corresponds to a standard deviation of the internal state of the $i$th neuron in ordinal Adachi & Aihara CNN.

3. Continue to update the system based on Eq. (11) until the system accesses to the basin of the target pattern corresponding to the fragment. If the system cannot accesses within $21 (= P \times L)$ steps, we regard that the system misses to accesses.

4. Update the system based on Eq. (4) and back to the procedure 2. In the evaluation of the
sensitive response, we check the sensitivity of chaotic associative memory dynamics at each time step. Therefore, by updating the system once based on Eq. (4), we change a chaotic associative memory dynamics with one iteration step and we check the sensitive response to a memory pattern fragment for the updated chaotic associative memory dynamics with the procedure 2.

5. The cycle of procedures from 2 to 4 are repeated $T$ steps.

The standard deviation $\sigma_i$ is introduced to enable us compare the results of the sensitive response for various $\alpha$. In addition, the standard deviation $\sigma_i$ does not play an important role in realizing sensitive response. In this paper, therefore, we evaluate the standard deviation $\sigma_i$ a priori, by observing the
system dynamics for each $\alpha$.

In an evaluation of the sensitivity, we employ two quantities as follows:

- **Success ratio**: How many times does the system reach the target basin within 21 steps starting from different points of the orbit of the chaotic associative memory dynamics? The success ratio is averaged value at $T$ different points.

- **Access time**: How many steps does it take to reach the target basin within 21 steps starting from different points? If it cannot reach within 21 steps, we set the access time to be 21 steps. The access time is also averaged value at $T$ different points.

In the calculation of the sensitivity we set $T_0 = 15,000$ and $T = 100$ steps. We evaluate the sensitivity for three kinds of $\rho$, 0.1, 1.0, 10. As the memory pattern fragments, we employ $10 \times 6$ (60/600) pixels of the common region among each cycle pattern. Several examples of the memory pattern fragments for the patterns with 0% and 100% randomness are given in Fig. 6. We start the calculation from the A1 pattern as an initial configuration of Adachi & Aihara CNN.

The results are almost the same for three kinds of $\rho$. Therefore, we present the results for $\rho = 10$. The results of the success ratio and the access time are given in Figs. 7 and 8, respectively. The behavior of the success ratio and the access time is similar to that of the visiting measure and the information dimension.

Since we start the calculation from the A1 pattern, the system is in the cycle pattern A for small $\alpha$. Therefore, the system certainly reaches to the target pattern with 1 step when the memory pattern fragment of the A1 pattern is injected. On the other hand, when the memory pattern fragment of B1 or C1 pattern is presented, the system misses, and then the access times takes 21 steps. Thus, the success ratio takes $1/3$ and the access time takes $(1 + 21 + 21)/3 \approx 14.3$ regardless of the degree of the randomness. In the case of the patterns with 100% randomness, for $0 \leq \alpha \leq 0.18$, the success ratio takes $1/3$ and the access time takes 14.3.
Fig. 7. Success ratio to the target memory pattern. (a) 0% randomness. (b) 10% randomness. (c) 20% randomness. (d) 30% randomness. (e) 40% randomness. (f) 50% randomness. (g) 60% randomness. (h) 70% randomness. (i) 80% randomness. (j) 90% randomness. (k) 100% randomness.

Subsequently, as $\alpha$ becomes larger, the behavior is different between 40% and 50% randomness. For the patterns with the randomness of smaller than 40%, the success ratio does not become too large and the access time also does not become too short. On the other hand, for the patterns with the randomness of larger than 50%, the success ratio becomes larger and the access time becomes shorter. In the case of the patterns with 100% randomness, at $\alpha = 0.75$, the success ratio suddenly becomes larger and the access time also becomes shorter. For $0.76 \leq \alpha \leq 0.96$, the success ratio takes 1. At $\alpha = 0.76$, the access time takes 2.94 and at $\alpha = 0.96$ the access time takes 2.04. The minimum access time takes 2.00 at $\alpha = 0.95$.

As the randomness becomes larger, the success ratio becomes larger and the access time becomes shorter. Therefore, the randomness plays an important role to realize the sensitive and robust response.
to the memory pattern fragments.

5. Discussions
As the randomness increases, for each cycle pattern, the basin volume becomes large, the visiting measure with almost the same frequency becomes larger than the spurious pattern and the response property of the chaotic associative memory dynamics to memory pattern fragments becomes more sensitive and robust. In addition, the overlap among inter-cycle patterns becomes quite smaller than intra-cycle patterns. Therefore, the randomness introduces the small overlap among inter-cycle patterns, and the fact is important to realize the sensitive and robust response to the memory pattern fragments.
However, it is a further problem why the basin volume of each cycle pattern becomes larger as the randomness increases. According to our various preliminary experiments, we got the result that the firing rate close to 0.5 is not important to realize larger basin volume of each cycle pattern. For instance, we evaluated basin volume of each cycle pattern with the almost 0.5 firing rate but without randomness. Unfortunately, the basin volume was quite smaller than the spurious one. On the other hand, it is easy to understand the relation between the basin volume and the visiting measure. For highly developed chaotic associative memory dynamics, which is almost similar to a random walking, the visiting measure becomes the almost same as the basin volume. Thus, the larger visiting measure of each cycle pattern than that of the spurious one indicates that it is easier to access to the attractor basin of each cycle pattern than that of the spurious one. In other word, the system with the larger visiting measure of each cycle pattern than that of the spurious one enable us to realize the larger visiting measure of each cycle pattern.

One of our answers how to construct the hierarchical memory patterns, whose basin volumes and visiting measures are sufficiently large, is as follows: Based on our results, we construct patterns with a hierarchical structure of two level as shown in Fig. 9. Each pattern indexed by “A,” “B” or “C” has a common region, referred to as genus A, B or C, respectively. The patterns in each genus is divided to two patterns, which is named as a species, indexed by “1” or “2”. The patterns in each species also has an specific common region. Remaining pixels of each pattern is different and is generated
Fig. 10. Overlap between the A1-1 pattern and the others. “A1”, “A2”, ··· and “C2” indicate species (corresponding to cycle) indexes and “1”, “2”, ···, “7” describe pattern indexes in each species.

Fig. 11. Basin volumes. (a) For each cycle pattern. (b) For total memory cycle and the pseudo cycle. “A1”, “A2”, ··· and “C2” indicate species (corresponding to cycle) indexes, and ‘D’ represents the spurious pattern.

randomly. Therefore, we denote each pattern by A1-1, ···, A2-1, ···, or C2-7. Note that a certain species corresponds to one of cycle patterns. In these patterns, the overlap among the same species is larger than the same genus and different genera as shown in Fig. 10. In addition, the overlap among the same genus is larger than different genera. This attribute of the overlap means a name of the hierarchical structure of two levels.

Finally, we evaluate a basin volume of these patterns. Considering the patterns in one spice as one cycle pattern, we embedded 6 cycle patterns into RNN. The result is given in Fig. 11. Although the basin volume of each memory pattern is slightly smaller than the spurious pattern, total basin volume of all the memory patterns is much larger. Therefore, we expect that we could realize sensitive response to memory fragments with use of these patterns. In near future, we will investigate the sensitive and robust response.

6. Conclusions

In the present paper, we investigate roles of the randomness of cycle memory patterns in realizing their large basin volumes and large visiting measure, and the sensitive response of the chaotic associative memory dynamics to memory pattern fragments. Results are as follows:

- As the randomness increases, the basin volume of each cycle pattern becomes larger and that of the spurious pattern becomes smaller. In addition, the total basin volume of all the cycle
patterns becomes quite larger than the spurious pattern.

- As the randomness increases, the visiting measure of each cycle pattern becomes almost the same and the visiting measure is larger than the spurious pattern in the region of $\alpha$ where the information dimension takes a large value.

- As the randomness increases, the success ratio becomes larger and the access time becomes shorter, meaning that sensitive and robust response of the chaotic associative memory dynamics to memory pattern fragments are realized.

- As the randomness increases, the overlap among inter-cycle patterns becomes much smaller than intra-cycle patterns.

From the results, the randomness plays an important role to realize the features as mentioned above, which introduce small overlap among intra-cycle patterns. In near future, we will present a sensitivity for the hierarchical patterns given in Fig. 9.

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