Multiplexed spatiotemporal communication model in artificial neural networks

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To cite this article:

Abstract: It is well known that there is intercommunication among the different areas of the brain. However, till date, the rules of communication have not been successfully analyzed. The spike trains from neuronal cells have been simply treated as density-modulated waves with an activation level of the corresponding neuronal cells, or, at most, they have been analyzed using traditional metrics between sequences. The spike trains from neuronal cells have a random-like pattern that provides few clues regarding a coding rule. Here in a randomly generated artificial 3 × 3 multiplexed spatiotemporal communication neural network composed of threshold elements, we showed that pseudorandom sequences were generated during the simulation, similar to the random sequences generated by the cultured neural network of the rat brain. The transiently generated sequence patterns in the simulation were regarded as reflecting the circuit structure. These randomly shaped circuits generated pseudorandom sequences that functioned as codes for multiplexing communication. Although the circuit weights are randomly generated at present, it will be possible to extend this approach to determine the network weights by learning. This paper provides simulation results that support findings on cultured neural network.

Keywords: M-Sequence, Neural Network, Pseudo Random Sequence, Spatiotemporal Communication, Spike Train

1. Introduction

We have developed a time-shift diagram method [1] for visualizing the propagation of brain waves. Figure 1 shows an example of a time-shift diagram in which the transmissions of magnetoencephalography (MEG) waves for a number counting task are shown with propagation times of less than 5 [ms] (in red; mainly within each hemisphere) and more than 10 [ms] (in blue; mainly across the callosum) [2]. Propagation times of 5–10 [ms] are indicated in green. When compared with the MRI dipole diagram method, which shows only a small number of major flows, our method follows an even smaller flow of signals. Questions arise as to how neuronal cells find their target cells and how the target cells obtain the necessary signals from the source neurons even if they are located at remote positions. Such multi-access communication requires codes. This issue served as the motivation for our research. However, till date, the rules of communication in the brain have not been successfully analyzed. The spike trains from neuronal cells have been treated simply as density-modulated waves with an activation level of the corresponding neuronal cells, and, at best, they have been analyzed using traditional metrics between sequences and from the viewpoint of spatial independent information.

1.1. Research on Spike Coding

To analyze spike trains, metrics between spike trains have been proposed via an alignment of distances and convolution metrics, including traditional rate coding [3]. However, the coding scheme of neurons has not been solved.
1.2. Spatiotemporal Coding

The extension of signals in a multidimensional manner permits dealing with many spatiotemporal patterns in artificial and natural neural networks [4-7]. In the visual system in particular, directional receptive fields, as seen in mammalian simple cells, emerge by a minimum information criterion [8] and an independent component analysis [9] for natural and facial images, i.e., spatially independent basis functions are derived by self-organization. Figure 2 shows how the receptive fields of the visual system are obtained by self-organization of the neural circuit with mutual inhibition to output only independent components [10]. Thus, it is reasonable to seek the temporally independent components of information representation in the brain as a pair of spatially independent components or seek the spatiotemporal information representation and communication coding scheme.

1.3. Pseudorandom Codes from Cultured Neural Networks

We have been analyzing the spike train structure of cultured neural networks to clarify intelligent processing in the brain [11-13]. We have decoded the spike trains of several samples of neural networks cultured on 8 × 8 multi-electrodes. From these, we observed significantly more M-sequences than observed from interval shuffled trains, which are representative pseudorandom sequences.

The question as to why neuronal spike sequences have a white-noise like pattern, such as M-sequences, then arises. Although many researchers have been tackling this problem, it has not yet been solved. The objective of this study is to support these in vivo data via simulation.

The remainder of this paper is organized as follows: After presenting some background information in Section 2 (as well as in the Appendix), we propose a 3 × 3 spatiotemporal communication neural network model in Section 3 and present a discussion and conclusions in Section 4.

2. M-Sequence

An M-sequence is an important basis of communication theory and systems [14-17]. The electrical 3-cell linear feedback shift register (LFSR) shown in Fig. 3 cyclically generates the M-sequence “0010111” of length 7. The operation in the figure is performed by exclusive OR (xOR) according to the standard theory. Although there are some exceptional xOR neurons [18], this may be equivalently realized by the combination of threshold elements as a standard neuronal model. One such example is shown in the Appendix.

The length of the M-sequence generated from n-cell LFSR is $2^n - 1$. In the case of a 3-cell LFSR, only one type of M-sequence exists, with the exception of mirror order and rotationally shifted sequences. We refer to this as M3, which is shown in Table 1. Table 1 also shows a 4-cell case (M4).
become temporally independent components of information transmitted to larger loops in the intelligent network [19-22]. Furthermore, systems, such as CDMA mobile phones, and may also be used as codes in real communication. M-sequences are often used as codes in communication. Each neuronal cell denoted by ○ works as a threshold-element (cell) network. Figure 4 shows the simplest model of $2 \times 2$ spatiotemporal multiplexed communication. Figure 5 shows a simple $3 \times 3$ communication model. With regard to the general behavior of synchronous threshold element networks, please refer to the Appendix.

### 3. Communication Model in a Neural Network

#### 3.1. Simplest Model

We can simulate brain neural networks as threshold-element (cell) networks. Figure 4 shows the simplest model of $2 \times 2$ spatiotemporal multiplexed communication. Each neuronal cell denoted by ○ works as one of these threshold elements in a synchronous mode, such that if the sum of the weighted inputs to the element is more than 0, it outputs “1,” otherwise it outputs “0.” Therefore, input “1” to $n_1$ is transmitted only to the opposite destination cell $n_3$, and input “1” to $n_2$ is transmitted to $n_4$.

Loop-shaped circuits, such as a LFSR, may become components of a large network or provide insights into the main loop in the intelligent network [19-22]. Furthermore, M-sequences are often used as codes in real communication systems, such as CDMA mobile phones, and may also provide insights into the main loop in the intelligent network [19-22].

<table>
<thead>
<tr>
<th>No. of Cells $n$</th>
<th>Regular / Reversal</th>
<th>Number and Comment</th>
<th>M-Sequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>Reversal (Rev)</td>
<td>(1) 1101000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2) mirror of (1)</td>
<td>1011000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Regular (Non-Rev)</td>
<td>(3) 0010111</td>
<td>0100111</td>
</tr>
<tr>
<td></td>
<td>(4) mirror of (3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Reversal (Rev)</td>
<td>(5) 11101001010000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6) mirror of (5)</td>
<td>101001110110000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Regular (Non-Rev)</td>
<td>(7) 00010011010111</td>
<td>010100100111</td>
</tr>
</tbody>
</table>

As shown above, we can simulate brain neural networks using threshold element networks. In Fig. 5, we show a simple $3 \times 3$ communication model. With regard to the general behavior of synchronous threshold element networks, please refer to the Appendix.

#### 3.2. $3 \times 3$ Spatiotemporal Multiplex Communication

Here, signal “1” sent from cell $n_3$ is not supposed to be received by $n_{18}$, that sent from $n_6$ is supposed to be received by $n_{25}$, and that sent by $n_{13}$ is supposed to be received by $n_{26}$.

Figure 5. A $3 \times 3$ communication model. Pulse “1” sent from neuron $n_3$ is supposed to be received only by $n_{13}$, that sent from $n_6$ is supposed to be received by $n_{25}$, and that sent by $n_{13}$ is supposed to be received by $n_{26}$.

We generated networks with random weights ($\in \{+1, 0, -1\}$) and selected those that satisfied the requirements mentioned above. We generated $2.012 \times 10^8$ networks in which each weight on the main loop was bidirectionally fixed to +1, i.e., weights from $n_3$ to $n_6$ and $n_6$ to $n_3$ were +1, and so on. Other weights were randomly fixed to +1, 0, and −1, with probabilities of 1/3 for each.

All cells in the network were synchronously driven. A single pulse “1” was given to the $n_1$ cell at time 1, and the output number of “1” was counted between time 1 and 16 at the $n_{18}$ cell. Effectively, the count was between times 8 and 16 at the destination cell because the pulse arrived at time 8. If the number of output “1” is the largest among $\{n_{18}, n_{13}, n_{18}, n_{23}, n_{28}\}$, successful communication is achieved for the test of the $n_3 \rightarrow n_{18}$ channel. If the three communication channels of $n_3 \rightarrow n_{18}, n_6 \rightarrow n_{25}$, and $n_{13} \rightarrow n_{28}$ are all successful in the same network, we classified the network as being...
successful in the $3 \times 3$ multiplex communication.

We obtained 141 successful networks with the desired function, i.e., the success rate was $7.01 \times 10^{-7}$ or, in other words, one network per $1.43 \times 10^6$ randomly generated networks exhibited $3 \times 3$ spatiotemporal multiplex communication.

Figure 6 shows an example of a successful network. Figure 7 shows the flow of the codes that worked as markers of the information flow; almost all sequences generated from a cell were transient within the short time of the communication and were too long to analyze. Thus, to visualize the information flow, we selected several remarkable short codes with length $\leq 7$ from the observed propagating wavefront sequence. We marked sequences “1011,” “10101,” “11111,” and “0010111.” “1011” is a core part of the reversal M-sequence “1011000;” “10101” is a typical alternating sequence of “0” and “1;” “11111” is a representative of long continuous “1” sequences; and “0010111” is a conventional non-reversal M-sequence.

Input stimulation to one of $\{n_3, n_8, n_{13}\}$ was encoded by the corresponding cell assembly $\{A_1, A_2, A_3\}$ and spreads in both directions to the right and left of the loop. Sometimes they were transformed to another code at the passing cell assembly, decoded at the destination assembly, and transmitted to the destination cell. If the coming sequence is not for its assembly, the assembly does not take it in but passes it to the next assembly.

Figures 8 and 9 show another example. Here, a conventional non-reversal M-sequence, “0010111,” and reversal M-sequences, “1010001” and “0100011,” were generated by the initial source input pulse “1” to the $n_{13}$ cell.
However, only the first code contributed to the output via an anticlockwise rotation route, whereas latter codes via a clockwise rotation route did not contribute. The maximum output was given from the destination cell $n_{28}$.

![Figure 9. State-transition diagram of the communication network shown in Fig. 8. “1” is given to $n_{13}$, which is internally encoded to the M-sequences “0010111,” “1010001,” and “0100011.”](image)

The temporal response function (time gate) at the receiving cell is shown in Fig. 10. In the case of a wide time gate, the number of “1s” at the destination cell is effectively counted after time 8, which represents the fastest arrival time of the pulse.

![Figure 10. Time gate weights at a receiving cell. Time 8 is the fastest arrival time of the pulse at the destination cell. In the case of a single time gate, only time 14 is shown. Double and triple time gates, which are the central part of LI-type gates, are not shown.](image)

### 3.2.2. Medium Time Gate

In the network described in Section 3.2.1, the gate only counted the number of pulses that arrived at the destination cell during the observation period from time 1 to 16. In the medium time gate, we restricted the arrival period at the receiving cell, i.e., the “1s” that arrived at times 15 and 16 were counted as penalties, and their number was subtracted from the number of “1s” that arrived between times 1 and 14 (roughly counting pulses between time 8 and 12; see Fig. 10 Medium). We obtained 222 successful networks from the $2.295 \times 10^8$ generated candidate networks. The success rate was $9.67 \times 10^{-7}$, or, in other words, one network per $1.03 \times 10^6$ generated candidate networks met the required communication function. This figure was higher than that of the wide time gate network and those of the medium time gate as an ensemble. However, because the appearance rates had large standard deviations, the average difference was not particularly important. In other words, there are many ways to realize a given task, as shown by the large standard deviations depicted in Fig.12, and the appearance rate reflects the structural difference only as an average.

![Figure 11. Major code spectrum of wide and medium time gate communication networks](image)

### 3.2.3. Single Time Gate

In this case, we imposed a restriction of the time gate to specific single times of 8, 9, 10, 13, and 15. The corresponding success rates are shown in Fig. 12.

![Figure 12. Success rate of a random network for the communication tasks](image)

### 3.2.4. Double and Triple Time Gates

In case of a double time gate, we combined two single time gates, such as D8–9, D9–10, D10–11, and D12–13. The corresponding success rates are shown in Fig. 13; the success rates of the double time gate are close to the average of the corresponding single time gates. Furthermore, we combined three single time gates, such as T9–10–11. In this case, the success rate was higher than that of each of the corresponding single time gates.
3.2.5. Lateral Inhibition (LI) Type Time Gate

Because the LI-type response is universal in natural neural networks, we applied it to the time response of the receiving cells.

The central peak was fixed to weight 1 and width 2. The central positions were taken at times 8–9, 9–10, 10–11, and 12–13. Four negative bases on both sides were set at a weight of −0.5. However, because the pulse arrived first at the destination cell at time 8, the front negative bases before time 8 were moved to the tail, as shown in Fig. 10. Each weight from time 8 to 16 was:

\[
\text{LI8–9} = (1, 1, -0.5, -0.5, -0.5, -0.5, 0, 0, 0)
\]
\[
\text{LI9–10} = (-0.5, 1, 1, -0.5, -0.5, -0.5, 0, 0, 0)
\]
\[
\text{LI10–11} = (-0.5, -0.5, 1, 1, -0.5, -0.5, 0, 0, 0)
\]
\[
\text{LI12–13} = (0, 0, -0.5, -0.5, 1, 1, -0.5, -0.5, 0).
\]

The code spectrum obtained is shown in Fig. 14. Some average differences existed between these LIs. However, the standard deviations were close to these averages; therefore, we could only observe almost random pulse sequences. The situation was the same in the cases of a single time gate described in 3.2.3 in which the spectra were almost the same as those shown in Fig. 14.

3.2.6. Time Shift Gate

The time-gate settings described above may create a bias to give the destination cell the maximum output, while potentially giving the non-destination cell located nearest to the source cell a lower output for pulses arriving through the shorter main loop route. To compensate for this bias, we shifted the center of the time gate of the halfway cells by 2, 4, and 6 according to the distance from the source cell. However, this remains incomplete at the point at which the pulses arriving through the longer main loop route are neglected.

3.3. Success Rate for Communication

We randomly generated networks, and if the network randomly gave the communication pair, the success rate ideally should become \(5^{-3} = 1.6 \times 10^{-3}\). However, the success rate of these networks with regard to communication was significantly different according to the type of time gate, as is shown in Figs. 12 and 13. The success rate of the wide time gate was the worst. In this time gate, there was no restriction on the arrival time of pulses, and only the pulses arriving at the receiving cell were counted. Single time gates, double time gates, and triple time gates had a better success rate. Among these, the faster time gate was relatively good. The LI-type time gates had the best success rate. In cases of LI9–10, LI10–11, and LI9–10–11, the success rate was approximately \(10^{-3}\). The improvement in detectability according to the time-gate shape had two effects on the success rate. One is the direct effect of raising the success rate. The other is lowering the success rate by raising the detectability of non-destination cells.

Figure 13 shows the success rates of time shift gates for double-type, triple-type, and LI-type time gates. LI-type time gates seemed to be sufficiently powerful for detecting the proper sequence. The time shift gates raised the detectability of non-destination cells, thus reducing the success rates. This shows that a bias of the time gate adjusted for destination cells helped detection at the destination cell. Figure 15 shows an example of a state-transition diagram of an LI-type time shift gate case.

The success rates of all time gates were lower than \(5^{-3}\) of the ideal random channel selection. The reasons for this observation may be that the random lines are sometimes disconnected, the network outputs the same levels, and the three directional tasks are not independent. However, LI-type reception is commonly effective in spatiotemporal communication with high success rates close to the ideal rate as well as in other general neural networks.

Figure 14. Code spectrum with standard deviation on the main loop of LI-type time gate communication networks

The weight of the LI-type triple time gate was set as LI9–10–11 = (−1, 1, 1, 1, −0.5, −0.5, −0.5, −0.5, 0).

Figure 15. Example of a state-transition diagram for a stimulation where “1” is given to \(n_{13}\) and an LI-type time shift gate is used
4. Discussion and Conclusions

We believe that the communication function between neuronal cells provides a basis for the intelligence functions of the brain, such as memory, association, and abstraction. However, to date, the neuronal spike trains have been treated as random noise-like signals, and the coding scheme of the natural neural network has not been completely elucidated. We have been tackling this issue from a communication engineering viewpoint and have proposed a model of spatiotemporal multiplex communication. In this model, each cell works as a transmitting/receiving cell and as a relay cell, the roles of which are I/O and intermediate communication, respectively. In this sense, the network works like a multi-hop ad hoc communication network.

Although only the shape of the network is given by $3 \times 3$ spatiotemporal multiple communication loop types, various network shapes can be considered; for example, a homogeneous network without a pre-assigned loop. Moreover, there are various ways to determine the task of the communication, i.e., various possible network shapes can have additional routes to the destination and timings. This represents a problem of balance between space and time.

We have shown that the simulated pulse sequence from each cell of the threshold element network resembled our experimental data, including the code spectrum. However, though not shown here, our experimental data were obtained in an unsorted state, including a single neuronal cell, and several neuronal cells and cell assemblies, such as synfire chains [23,24], which may cause synchronous spikes, including codes. Codes may be composed from these cell “groups,” which represents an open problem.

We obtained target networks via random generation and selection. Although this method is useful to demonstrate the feasibility of such communication tasks, it is ineffective in real situations because of necessary computational capacity. In the brain, target networks are considered to be formed by learning. Therefore, we are now developing such networks based on learning. In addition, noise immunity, interference effects between communication channels and successive transmissions, and stability should be investigated. However, the objective of this paper is to demonstrate the feasibility of spatiotemporal multiplex communication in neural networks, and we believe we were able to show its feasibility using a minimum-size model.

The content of this paper can be summarized as follows:

1) A neural network with a spatiotemporal communication function was proposed.

2) Each neuronal cell worked as a transmitting and receiving cell as well as a relay cell.

3) Pulses running in the network seemed to be like noise, similar to the code observed in naturally cultured neuronal networks.

Appendix

Here, we present some results of an output analysis, particularly for the M-sequences included in the state transition output of each threshold element of the network in general.

Figure A1. Output analysis of threshold cell network

Figure A2. State transition of the network

Figure A1 shows the method used to analyze the output of the network. At time $t = 1$, a single stimulation “1” is given to cell $U_i; i \in \{1, 2, \ldots, n\}$, where $n$ is the number of cells. Cell $U_j; j \in \{1, 2, \ldots, n\}$ gives an output of “0” if the sum of the weighted input given to $U_j$ is $\leq 0$ and “1” if this sum is $> 0$ synchronously in the network. The threshold is 0 unless otherwise specified. Each weight is +1, 0, or −1. Generally, the state expressed by the combination of all cell states (“0” or “1”) changes with time, as shown in Fig. A2.

A1. Four-Cell Network

In this case, all possible $3^{16} = 43,046,721$ networks could be generated non-randomly as a treatable maximum number. Although we did not use this approach, this number may be reduced by using the symmetric characteristic of the weights. Instead, stimulation was given only to a fixed cell, e.g., $U_1$. 
The average number of cycles of state transition per network is shown in Fig. A3. Period 1 means that the state did become stationary. Some networks generated an M-sequence (see Fig. A4 for an example). The $i,j$ entry of matrix $C$ shows the connection weight from $N_j$ to $N_i$. The output sequence from $N_1$ is “1001110”, which is an inverse-order, rotationally-shifted, and non-reversed version of the M-sequence “1101000” listed in Table 1.

**A2. Number of M-Sequences Detected**

The output from each cell was checked among 32 clock times after stimulation. Then, the total number of $1.34 \times 10^{10}$ positions on the sequences was checked. The detected M-sequences are shown in Table A1, in which (1)-(4) correspond to those listed in Table 1. In this case, the rate of Non-Rev was larger than that of Rev.

**A3. Twelve-Cell Network**

In this case, we were no longer able to check all networks. Thus, we generated networks with various weights {+1, 0, −1}, as shown in Table A1. By changing the stimulation cell, the output from each cell was checked among 64 (practically 52 time positions) clock times after the stimulation.

### Table A1. Rate of M-sequences detected

<table>
<thead>
<tr>
<th>No. of Cells $n$</th>
<th>Possible Networks</th>
<th>Rate of Weights +1, 0, −1</th>
<th>Generated Networks</th>
<th>Sequence Positions Checked $\times 10^6$</th>
<th>Rev [(1), (2)] $\times 10^{-5}$</th>
<th>Non-Rev [(3), (4)] $\times 10^{-5}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>$3^{16}$</td>
<td>(All Checked)</td>
<td>$3^{16}$</td>
<td>13,400</td>
<td>6.61</td>
<td>16.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Equivalently</td>
<td></td>
<td></td>
<td>(4.47, 2.14)</td>
<td>(5.00, 11.6)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1/3, 1/3, 1/3</td>
<td></td>
<td></td>
<td>$\times 10^{-5}$</td>
<td>$\times 10^{-5}$</td>
</tr>
<tr>
<td></td>
<td>0.4, 0.2, 0.4</td>
<td>6000</td>
<td>44.9</td>
<td></td>
<td>12.0</td>
<td>9.95</td>
</tr>
<tr>
<td></td>
<td>0.3, 0.4, 0.3</td>
<td>6000</td>
<td>44.9</td>
<td></td>
<td>(6.08, 5.89)</td>
<td>(4.88, 5.07)</td>
</tr>
<tr>
<td>12</td>
<td>$3^{144}$</td>
<td>0.1, 0.8, 0.1</td>
<td>3000</td>
<td>22.4</td>
<td>1.53</td>
<td>0.912</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Equivalently</td>
<td></td>
<td></td>
<td>(0.785, 0.749)</td>
<td>(0.456, 0.456)</td>
</tr>
<tr>
<td></td>
<td>0.15, 0.8, 0.05</td>
<td>23,000</td>
<td>172</td>
<td></td>
<td>3.32</td>
<td>2.94</td>
</tr>
<tr>
<td></td>
<td>0.06, 0.92, 0.02</td>
<td>9,000</td>
<td>67.4</td>
<td></td>
<td>(1.56, 1.76)</td>
<td>(1.69, 1.25)</td>
</tr>
</tbody>
</table>

Figure A5 shows a time flow for the case of the weight rate of (0.1, 0.8, 0.1). Here, “Theor” represents the theoretical values calculated for cases in which the observed sequence was white random (no correlation within the sequence) and the observed “0” and “1” rates were used at each time position. The observed rates of the M-sequence code were rather low, with the exception of the initial time area. This means that the states at the initial time area are transient and close to the random state. In addition, after some time, the states shift to steady states that include final cyclic states, most of which are not M-sequence cycles, but are shorter (such as “1111111,” “0000000,” or “101010101”).
Figure A5. Number of M-sequences detected per cell and time. Symbols correspond to those listed in Table 1. "Theor" refers to the theoretical values under the assumption of a random sequence. Curves of Theor-(1) and (2) almost overlap. Curves of Theor-(3) and (4) also almost overlap.

As a result, we can say that there was a tendency for the rate of Rev M-sequences, including those that are fragmental, to be greater than that of Non-Rev sequences. In addition, information from the source cell was included in the early transient period. This explains why we analyzed only the wavefront in this study.

Acknowledgements

The authors are grateful to Dr. T. Shimosakon of Osaka Institute of Technology for his support and advice.

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