

Reservoir Computing with Complex Cellular Automata

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Abstract

Reservoir Computing is a computational framework in which a dynamical system, known as the *reservoir*, casts a temporal input signal to a high-dimensional space, and a trainable *readout layer* creates the output signal by extracting salient features from the reservoir. A suitable reservoir must possess the property of *fading memory* in order to process inputs. The foundations of Reservoir Computing are the independently proposed Echo State Networks and Liquid State Machines, both of which use a randomly connected artificial recurrent neural network as the reservoir. Since the inception of the field, researchers have looked for ways to optimize the selection of reservoir construction parameters. Hierarchical reservoirs reimpose a degree of topological structure on reservoir connectivity by breaking the monolithic reservoir into loosely connected sub-reservoirs. The realization that dynamical systems besides neural networks could act as reservoirs has caused increasing interest in alternative reservoir substrates using biological, chemical, and physical dynamical systems. Several researchers have experimented with using the dynamical behavior of elementary cellular automaton rules as reservoirs. This research described in this paper expands this approach to cellular automaton with larger neighborhoods and/or more states, which are termed complex, as opposed to the elementary rules. Results show that some of these non-elementary cellular automaton rules outperform the best elementary rules at the standard benchmark 5-bit memory task, requiring half the reservoir size to produce comparable results.

1 Introduction

The small field of Cellular Automaton based Reservoir Computing (ReCA) has focused so far on the 256 elementary one-dimensional Cellular Automaton (CA) rules which have two states and a neighborhood of size three. This work expands ReCA to include one dimensional CA rules with larger neighborhoods and more states. These rules that are not part of the set of one-dimensional elementary rules will be referred to as *complex* CA rules. CA rule performance is tested on the 5-bit memory task that is standard in ReCA research. More expressive rules that outperform any of the elementary rules require a smaller CA reservoir, reducing the amount of computation required to train the output layer and to operate the reservoir.

The remainder of the paper is organized as

follows. Section 2 presents background information on Reservoir Computing and Cellular Automata. Section 3 outlines the ReCA system architecture used in the experiments. The benchmark task used to evaluate the CA rules is described in Section 4. Section 5 lists the complex CA experiments performed. Sections 6 and 7 provide results and discussion. Future work is discussed in Section 8, and Section 9 concludes the paper.

2 Background

2.1 Reservoir Computing

Reservoir Computing (RC) is a relatively new approach to machine learning in which the inner dynamics of a recurrently connected system, the *reservoir*, are harnessed to cast temporal inputs into a high-dimensional space, en-

hancing their separability. A *readout layer* generates the output from a linear combination of the states of reservoir nodes. Figure 1 shows the components of a reservoir computing system. The idea of reservoirs as a new type of architecture for Recurrent Neural Networks (RNNs) was proposed independently in 2001, under the name Echo State Networks (ESNs) [1], and in 2002 as Liquid State Machines (LSMs) [2]. The recurrent connections of a RNN cycle information back to the internal nodes, allowing them to possess *state*, or memory, which makes them suitable for sequential tasks such as speech recognition. Unlike traditional neural networks, the internal weights between the nodes of the reservoir used in RC are not trained. Only the weights to the output, or readout, layer are trained, providing a substantial reduction in the amount of computation required for learning.

A reservoir capable of representing the inputs in its internal dynamics can perform multiple computation tasks, even simultaneous tasks, by training different readout layers to extract the output. In both the original ESN and LSM reservoir design nodes are connected at random, but as reservoirs found a growing number of successful applications, researchers examined alternate construction techniques [3] and showed that many types of system besides RNNs produce effective reservoirs [4].

In order for a reservoir system to perform useful computation, it must possess the *echo-state property*, characterized by the term *fading memory*. The system has the ability to remember (or echo) inputs, but also forgets them over time. The *echo-state property* guarantees that the input driving the ESN will “wash out” the influence of the random initial condition of the reservoir, causing it to react predictably to inputs [1]. Dynamical systems operating at the “edge of chaos” between ordered and disordered behavior are believed to possess the highest computational power [5][6].

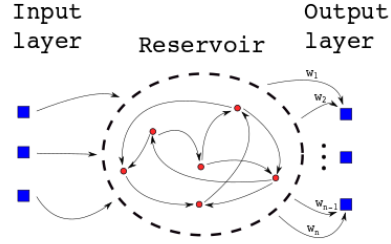


Figure 1: Components of a reservoir computing system. Input is connected to a subset of the reservoir nodes. Output is usually fully to the reservoir. Only the outout weights w_i for $i \in \{1, \dots, n\}$ are trained.

2.2 Cellular Automata

Cellular Automata (CA) are dynamical systems composed of discrete cells arranged in a grid of arbitrary dimension (usually one, two or three dimensional), where each cell is in one of a finite number of states. At each *generation* the cells are synchronously updated to a new state according to the CA transition rule, which is a function of the cell’s previous state and that of its neighboring cells.

The CA used in this paper are one-dimensional, which means that a cell’s neighborhood is a row of an odd number of contiguous cells, centered on itself and including the immediate neighbors to the left and right. Successive time steps are iterated downward to form a two-dimensional representation of the CA’s evolution through time. The rule space of a CA depends on the size of the neighborhood, N , and the number of states, S . The cell states are numbered from 0 to $S - 1$. The number of possible neighborhood states is S^N and each of these may be mapped by the transition rule to one of the S states, giving a total rule space of S^{S^N} . A CA rule is used as a look-up table to apply the transition from each possible neighborhood state. Figure 2 illustrates how a CA rule is applied.

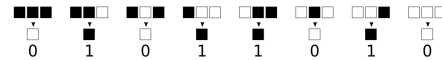


Figure 2: Elementary rule 90.

In his book *A New Kind of Science* Wolfram systematically investigated the 256 one-

dimensional rules with $S = 2$ and $N = 3$, which he named elementary cellular automata [7]. An elementary rule’s number is found by reading the rule as a binary number and converting it to base-10. Wolfram also proposed a classification system based on the complexity of the emergent behavior of a CA rule. Class I CAs rapidly evolve to an homogeneous state from most initial configurations. Class II CAs evolve to a stable or simple periodic pattern. Class III rules lead to chaotic behavior without stable structures. In Class IV rules “edge of chaos” behavior can develop, where localized structures can last for long periods, interacting with each other in interesting and difficult to predict ways. An instance of a Class IV rule, rule 110, has been proven to be Turing complete [8]. Figure 3 shows examples of the four classes.

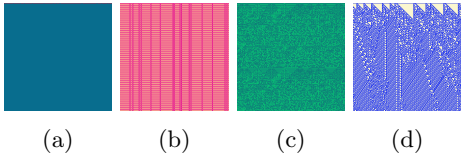


Figure 3: Wolfram’s four classes of Cellular Automata rule represented by the elementary rules. (a) Class I: Rule 215, (b) Class II: Rule 1, (c) Class III: Rule 105, and (d) Class IV: Rule 193.

3 Method

The ReCA system described in this section was implemented by the author in a C++ framework which can be found at <https://github.com/nbabson/CAreservoir>. The architecture of the framework is similar to that used in [9] and [10].

3.1 ReCA System Design

The CA reservoir is made up of R sub-reservoirs which receive identical temporal input signals. This technique of duplicating the reservoir has been used since the original ReCA paper, and is found to be necessary for accurate results [11]. The leftmost cell of the first sub-reservoir is set to be the neighbor of the rightmost cell of the last sub-reservoir, creating a single circular CA. Within each sub-reservoir a random mapping is generated between the elements of the input, of length L_n , and cells of

the reservoir. The sub-reservoir size is known as the diffusion length, L_d , where $L_n < L_d$. The random mapping diffuses the inputs into the larger sub-reservoirs.

The reservoir is initialized with all the cells in the same state, either 0 for a two state CA, or the highest numbered state if $S > 2$. The initial input overwrites select cell states, according to the mapping. For applications with binary input, such the 5-bit memory benchmark, this is done by replacing the initial state of the $R * L_n$ input cells with 0 or 1. The reservoir processes the input by the application of the CA rule for I iterations, creating a CA reservoir of $R * L_d * (I + 1)$ cells. The initial $R * L_d * I$ cells are vectorized to provide the input to the readout layer, while the last $R * L_d$ cells form the initial CA state for the next timestep, which is again selectively overwritten according to the input mapping. The rule is applied again, and the process repeats for each timestep of the input data.

Figure 4 illustrates how the input is encoded into the reservoir and expanded by the CA rule to create the output vector. The parameters S , N , R , L_d , and I can be set by command line arguments.

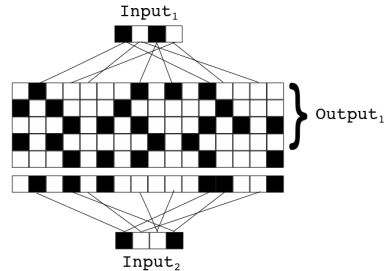


Figure 4: Mapping the input to the reservoir and generating the output. $L_n = 4$, $L_d = 8$, $R = 2$, $I = 4$, Rule 90. Initially all the cells of the reservoir are in the same state. At each timestep the input is randomly mapped onto each of the R sub-reservoirs, overwriting the cell state. The CA rule is then applied I times. The last generation of the CA forms the initial state for the next timestep, which is again overwritten according to the input mapping. The rest of the CA is vectorized and sent to the output nodes.

3.2 Readout Layer

The 5-bit memory task requires the network to predict three output bits per timestep. Accordingly, the ReCA system that performs it has

three output nodes. The weight from identical locations of the CA created at each timestep are treated equally, and used to predict output by reflecting the system’s response to inputs. The output weights from the $R * L_n * I$ ReCA cells to the readout nodes are set using a linear regression model. The outputs from all time steps, as well as the target values, are sent to the linear regression model all at once for fitting.

After the weights are set, the task is run again and the system predicts the outputs. The real-valued output of the linear regression at the output nodes is binarized, with output smaller than 0.5 rounded to 0, and equal or greater to 0.5 rounded to 1.

The ReCA system uses two different linear regression implementations, the linreg package from the C++ AlgLib library, and the linear_model.LinearRegression class from the Python scikit-learn library. The two implementations produced equivalent results but the sci-kit functions ran faster, so sci-kit is used for the experiments in this paper. The system also allows the option of using support vector machines (SVM) from the C++ Torch machine learning library as the classifier. Stefano Nichele and Magnus Gunderson used SVM in their 2017 ReCA paper on non-uniform reservoirs[12].

4 Benchmark Tests

4.1 Five Bit Memory Task

The 5-bit memory task benchmark tests a network’s long-short-term-memory capability, and has been shown to be difficult for recurrent neural networks, including ESN [13][14]. All of the literature on ReCA uses the 5-bit task benchmark, so it is an appropriate first test of the capabilities of complex versus elementary CA reservoirs. The task has four temporal binary input signals, i_1, i_2, i_3 , and i_4 , and three binary outputs, o_1, o_2 , and o_3 . During the first five time steps of one run of the input sequence, the i_1 input is one of the 32 possible five digit binary numbers, while i_2 is always $(i_1 + 1) \bmod 2$ (1 when $i_1 = 0$ and vice versa). This is the *message* that the system is supposed to remember. While the message is being input, $i_3 = i_4 = 0$.

This is followed by a *distractor period* of T_d timesteps. Following convention in ReCA research, all tests in this paper were done with $T_d = 200$. On all time steps of the distractor period except the last, $i_1 = i_2 = 0, i_3 = 1$, and $i_4 = 0$. On the last step of the distractor period, $i_4 = 1$, giving the cue signal that it is time for the system to reproduce the pattern. Up until this point the expected output is $o_1 = o_2 = 0$ and $o_3 = 1$. For the remaining five time steps of the run the output bits should be the same as the *message*, i.e. the same as the first three input bits during the first five time steps. While the message is repeated, the inputs are the same as during the distractor period, $o_1 = o_2 = o_4 = 0$ and $o_3 = 1$. Table 1 illustrates one run of the 5-bit task.

This series of $T_d + 10$ time steps is a single run of the test and is repeated for each of the 32 possible message inputs. To pass the 5-bit task the trained system must correctly predict the output bits for all steps of the task. With $T_d = 200$, that is $210 * 32 * 3 = 20,160$ accurate predictions.

Time step	Input				Output			
1	1	0	0	0	0	0	1	Input message
2	0	1	0	0	0	0	1	
3	0	1	0	0	0	0	1	
4	0	1	0	0	0	0	1	
5	1	0	0	0	0	0	1	
6	0	0	1	0	0	0	1	Distractor period
...	0	0	1	0	0	0	1	
204	0	0	1	0	0	0	1	
205	0	0	0	1	0	0	1	Cue Signal
206	0	0	1	0	1	0	0	Repeat Message
207	0	0	1	0	0	1	0	
208	0	0	1	0	0	1	0	
209	0	0	1	0	0	1	0	
210	0	0	1	0	1	0	0	

Table 1: Run 17 of 32 of the five bit memory task.

5 Experiments

In order to establish a baseline for the performance of the complex CA rules on the 5-bit memory task, the ReCA framework was tested on a selection of elementary CA rules which were found to be the most successful at the task in previous work[11][10]. With $I = 4$ and $R = 8$, only four elementary rules were able to achieve zero error on the 5-bit task. These four rules are equivalent, being either mirror

images of each other and/or having their states reversed.

Increasing the reservoir size by adding sub-reservoirs or applying the rule more times improved accuracy, but came at a cost of increased processing time required to perform the linear regression. Table 2 shows the results for the most promising elementary rules at different combinations of I and R. Table 3 gives average times to train and test elementary CA reservoirs of different sizes. The results obtained here were somewhat worse for the smaller reservoir of $(I,R) = (4,8)$ than in previous work using a similar system design [10][11][12].

Finding more effective rules among complex CA enables the task to be reliably completed with a smaller reservoir than is required by an elementary CA, thereby reducing the amount of computation required. All of the experiments described in this section were performed with $(I,R) = (4,8)$ and $L_d = 40$. Only rules that passed the 5-bit task on their first run were saved for further testing. Since none of the elementary CA rules were able to pass the benchmark as much as 10% of the time, this means that many rules which are capable of outperforming any of the elementary rules were rejected.

Rule	$(I,R)=(4,8)$	$(8,8)$	$(4,12)$
60	9	99	92
90	0	22	2
102	9	99	86
105	0	4	3
153	6	99	87
195	6	99	92

Table 2: Successful trials out of 100 for elementary CA rules on the 5-bit task.

(I,R)	Time
$(4,8)$	19 s
$(4,12)$	33 s
$(8,8)$	57 s

Table 3: Time in seconds to train and test a reservoir using elementary rule 60 on the 5-bit task for different values of I and R. Times are averages of five test runs.

5.1 Three State CA Reservoir

One dimensional CAs with three states and a neighborhood of three have a transition function specified by a lookup table 27 digits long. The rule space is $3^{27} \approx 7.6 * 10^{12}$. A stochastic search of the space randomly generated rules to test on the 5-bit memory task. As the most computationally intensive part of the search is performing the linear regression on the reservoirs, class I and class II rules, whose behavior is believed to be too simple to support computation, are removed. The CAs are first evolved according to their rule without any inputs beyond a random initial configuration. Rules for CA that settle into a uniform or oscillating state in the first 100 generations, as well as those that merely shift to the left or right, are removed from consideration.

The remaining rules are tested on the 5-bit memory task. Those that succeed without any inaccurate predictions are saved for further testing. These are then scored on 100 runs of the 5-bit task. Out of a thousand runs, rules that passed the benchmark were found 2.0% of the time, and 17.6% of the randomly generated rules were discarded as class I or II.

5.2 Neighborhood Five CA Reservoir

Two state neighborhood five rules have a rule space of $2^{32} \approx 4.3 * 10^9$. As with three state neighborhood three rules, this space was searched stochastically, with class I and class II rules ignored. Rules for reservoirs that pass the 5-bit memory task are saved and tested on 100 further runs of the benchmark. Of 1000 runs, 2.2% of randomly generated rules passed the benchmark, and 16.2% of the rules were rejected before testing for being class I or class II.

5.3 Population Density Rules

Population density transition rules are a function of a cell's state and the count of how many cells are in each state $s \in S$ among its neighbors. For $(S,N) = (2,5)$, these are a left-right symmetrical subset of the two state neighborhood five rules. The transition function lookup table is 10 digits long, and each of the 1024

rules were investigated. Those exhibiting class I or class II behavior were rejected while the rest were tested on the 5-bit memory task. Nine rules passed the benchmark. Those that passed were saved and tested on the benchmark 100 times.

5.4 Evolving Complex CA Rules

Complex CA with more than three states have a vast rule space. For $(S,N) = (3,4)$ and $(S,N) = (3,5)$ the number of possible CA rules are $\approx 3.4 \cdot 10^{38}$ and $\approx 2.4 \cdot 10^{87}$ respectively. These spaces are not amenable to a stochastic search for rules able to perform the 5-bit memory task. Hundreds of randomly generated rules failed to produce any that were successful. Almost all of these reservoirs mapped every input to the most frequently occurring expected output for each output layer node. This is because the vast majority of these rules are class III, too chaotic to allow stable structures too persist and therefore unable to support computation.

In order to reduce the chaoticity, a genetic algorithm (GA) was used to evolve rules more likely to have class III behavior. The very chaotic rules found by randomly generating a CA with $S > 3$ tend to have small contiguous regions in their two dimensional representation of development in time, resembling television static. The GA fitness function selects for rules more likely to have class IV behavior by maximizing the size of these contiguous regions, which allows for the possibility of developing stable localized structures.

The GA algorithm starts with a randomly generated population of 32 rules. At each epoch the rule is applied for 200 iterations to an initial random configuration of 400 cells. The fitness of each individual is evaluated using a “smallest-largest” rule. The largest contiguous region of cells belonging to the same state, adjacent horizontally or vertically, is identified for each state $s \in S$. The fitness assigned to the rule is equal to the size of the smallest of these largest connected areas. Using the area for the state whose contiguous region is smallest ensures that all the states contribute to the dynamic behavior of the CA rule and prevents the tendency for the GA to evolve toward a uniform class I behavior.

The least fit half of the population are dis-

carded and replaced by the next generation of offspring. The fit half of the population forms eight pairs that each produce two new rules by separating at a randomly chosen location and recombining, as seen in Fig. 5. Each new rule receives a single random mutation changing one digit of its rule. Evolution continues for 200 generations or until the fitness of the best individual equals or exceeds 200, which rarely takes more than 150 generations.

Both the mating and the mutation portion of the algorithm were found to be necessary, with either one removed evolution happens much more slowly if at all. The fitness goal of at least 200, for both four state and five state rules, was chosen empirically as the point where the evolved rules were making the least incorrect predictions when given the 5-bit task.

The evolved four state rules passed the benchmark 2.5% of the time and the five state rules passed 1.1%. Many more missed less than 10 predictions, which was not observed to happen with unevolved rules.

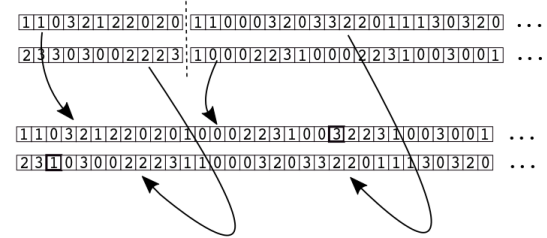


Figure 5: Two rules produce a pair of children by splitting at a randomly chosen point and recombining. Each child receives a single random mutation.

5.5 Non-Uniform Reservoir

A non-uniform CA is one in which the cells don’t all implement the same rule. The ReCA framework used here implements a parallel non-uniform CA in which the reservoir is split in half into two sub-reservoirs using different rules. The cells at the boundaries between the two sub-reservoirs consider their neighbors in the other sub-reservoir the same as those in their own sub-reservoir in the application of the rule. This allows information to flow between the two regions. Previous work has shown that certain combinations of elementary rules in a parallel ReCA perform better

than either of the rules individually at the 5-bit memory task while other combinations impeded performance[12].

In this work combinations of complex rules were tested together to show that complementary rule combinations exist for the different types of complex CA rules investigated.

6 Results

From each of the types of rules that were investigated, the six most successful rules at performing the benchmark task using reservoirs with parameters $(I, R, L_d) = (4, 8, 40)$ were selected for testing with smaller reservoirs. In the absence of a naming convention for the complex rules, these were given labels. The best performing rules and their labels are seen in Table 4.

The selected rules were then tested 100 times each with a range of the reservoir parameters I, R , and L_d . The results can be seen in Table 5.

7 Discussion

While the best performing elementary rules required a reservoir of size $I * R * L_d = 8 * 8 * 40 = 2560$ cells in order to achieve 99% success on the 5-bit memory task, each of the five categories of complex CA rule investigated here produced a rule capable of achieving 99% or 100% success on a reservoir of half that size, $I * R * L_d = 4 * 8 * 40 = 1280$ cells. The best performing rules discovered were three state neighborhood three. One of these was able to produce 100% correct results using a reservoir of size $I * R * L_d = 4 * 6 * 40 = 960$ cells. Only the neighborhood five population density rules were investigated exhaustively. For the other rule categories continued searching would yield a virtually infinite number of similarly successful rules.

Rule performance correlates broadly with reservoir size, but the ability of the ReCA system to pass the benchmark falls at different rates depending which of the reservoir parameters I, R , or L_d is lowered. The 30 complex rules average 91.7% correct test runs on the 1280 cell reservoir. Reducing the reservoir size by 1/4 by lowering the diffusion length to

30 caused the least performance degradation, with the average success rate at 56.6%. Reducing the reservoir size by cutting the number of sub-reservoirs from eight to six had a slightly larger effect on the average reservoir performance, which fell to 45.9%. Finally, when the reservoir size was reduced to 960 cells by lowering the number of iterations, I , from four to three, the average success rate was only 11.0%, with 11 rules achieving zero correct runs, while a couple of rules were relatively resilient to the reduced iterations. When the reservoir size was halved from 1280 to 640 cells, the majority of the complex rules were unable to complete any successful runs of the task, and the average success rate was only 1.9%.

An attempt was made to find pairs of rules that would complement each other in a non-uniform reservoir, performing better than either rule would alone, as has been shown to sometimes occur with pairs of elementary rules [12]. The six rules of each complex rule type can form 75 combinations of same-type rules each of which can be used as a non-uniform reservoir for any setting of the reservoir size parameters. Of these possibilities, 20 combinations were tested with 100 runs of the benchmark. Pairs of rules were selected that performed well individually with the same reservoir parameters. None of these pairs performed better than the more successful of the two in a uniform reservoir, 11 of the pairings performing significantly worse than either rule tested alone. While it seems very likely that complex CA non-uniform pairings exist which do work well together, it remains an open question how common or rare they are.

8 Future Work

The next step in investigating complex CA rules for ReCA would be to measure the chaoticity of the most successful rules in comparison to the average, using measures such as Shannon entropy, Langton’s λ parameter, and the Lyapunov exponent. It would be interesting to see whether the successful rules do tend to cluster in an “edge of chaos” region of complexity, and whether this is true for different benchmark tasks.

Other fitness functions could be explored

Three State Rules (S,N) = (3,3)	
$S3_1$	022001212222022121202001201
$S3_2$	212001112001100202012121112
$S3_3$	110211111111012011002221221
$S3_4$	112220001122200202101120022
$S3_5$	12000011121120121212222020
$S3_6$	210121202010220010012001002
Neighborhood Five Rules (S,N) = (2,5)	
$N5_1$	10011011100011011100011101100000
$N5_2$	00000000110011011101111101000000
$N5_3$	0111001001011111011001001000000
$N5_4$	1111101001110100110110100010010
$N5_5$	01001111011100010110000101010100
$N5_6$	0111000111101110001110101010111
Density Rules (S,N) = (2,5)	
D_1	0100111011
D_2	1001010100
D_3	1011010000
D_4	1111001010
D_5	1001110101
D_6	1010001101
Four State Rules (S,N) = (3,3)	
$S4_1$	2321222211000231312322232311322030112313011100201322000131220020
$S4_2$	3202120010220311333022122021303233302103221213012310122021121000
$S4_3$	0133030132200000320101302012232200212322332332000000130331110303
$S4_4$	2330232310230333132321011123101333310111101120123322023101112201
$S4_5$	1103233321313023211332211232000210133021222120002201022101311332
$S4_6$	1303200320121103303030201311010210331123101211201101121212023003
Five State Rules (S,N) = (3,3)	
$S5_1$	1301443104221322240300230403103441002312212144030011314304232243323124040221 4204330141121024304340424234410332033014231100030
$S5_2$	1203233110034020231023234244243332104432100104440412333033104430212221401123 430201402420031130100420020323323023204121113342
$S5_3$	1400243030402041101342340202043101140340113112143144030220022044324410141400 1144040240413332111020130224434041240241032000030
$S5_4$	1421333424244211231320221124334213323140314040030314242321304343413222403434 1443102441033314110213410404041140002414124400043
$S5_5$	34203133032322101243344342044403031133414314300043124201312322441210243102 0012332434010222311113213123044310440203144333200
$S5_6$	0133104314321000400141320442032240002333312104040024401313033202213203300242 3234304312240443431412304141033301200200241442030

Table 4: The six best rules from each of the categories of complex CA rule investigated.

for evolving CA rules towards a desired chaoticity. The existence of an “edge of chaos” region of complexity densely populated with successful rules would mean that reservoir rules could be constructed with the requisite degree of complexity at lower computational cost and greater accuracy than being evolved.

Further examination of non-uniform complex ReCA reservoirs could apply different types of rules in parallel i.e. rules with different

neighborhood size or number of states. Different types of rules may exhibit differing behaviors that in some circumstances synergistically combine in a beneficial manner. Measurements of rule chaoticity might also be able to shed some light on why certain combinations are complementary. It is also possible that given one successful rule, techniques for constructing a complementary rule could be discovered.

Rule	(I,R, L_d)=(4,8,40)	(4,8,30)	(4,6,40)	(4,4,40)	(3,8,40)	(4,8,20)
Elementary Rules (S,N) = (2,3)						
60	9	-	-	-	-	-
90	0	-	-	-	-	-
102	9	-	-	-	-	-
105	0	-	-	-	-	-
153	6	-	-	-	-	-
195	6	-	-	-	-	-
Three State Rules (S,N) = (3,3)						
$S3_1$	100	100	100	0	25	10
$S3_2$	99	63	44	0	16	0
$S3_3$	100	92	89	2	0	6
$S3_4$	100	53	42	0	0	0
$S3_5$	100	85	93	2	2	0
$S3_6$	99	97	79	6	5	0
Neighborhood Five Rules (S,N) = (2,5)						
$N5_1$	97	83	61	0	0	0
$N5_2$	99	92	60	0	0	2
$N5_3$	99	98	69	0	88	2
$N5_4$	95	75	59	0	0	0
$N5_5$	95	87	26	0	0	0
$N5_6$	93	49	46	35	38	0
Density Rules (S,N) = (2,5)						
D_1	68	47	23	0	1	0
D_2	70	0	6	0	0	0
D_3	94	62	63	0	0	20
D_4	96	87	57	0	0	0
D_5	99	17	35	0	25	0
D_6	64	58	27	0	1	0
Four State Rules (S,N) = (3,3)						
$S4_1$	90	75	58	0	12	1
$S4_2$	90	84	56	0	9	0
$S4_3$	93	12	9	0	42	0
$S4_4$	95	35	21	0	0	0
$S4_5$	100	85	66	0	11	1
$S4_6$	87	20	2	0	0	0
Five State Rules (S,N) = (3,3)						
$S5_1$	95	50	42	8	15	20
$S5_2$	95	76	70	0	7	0
$S5_3$	99	74	51	0	24	0
$S5_4$	80	1	9	0	2	0
$S5_5$	84	17	7	0	2	0
$S5_6$	77	13	6	0	5	0

Table 5: Successful runs out of 100 on 5-bit task for elementary CA and five types of complex CA rule.

9 Conclusion

A reservoir computing with cellular automata (ReCA) framework has been implemented which expands the field of ReCA research from the 256 elementary cellular automata rules to investigate rules with larger neighborhoods and more states, here called *complex* CA rules.

A genetic algorithm was used to reduce the chaoticity of the four state and five state rule space, in order to find *edge of chaos* rules capable of computing the 5-bit memory task benchmark.

The six best rules from each of five categories of complex rule were tested and shown to require half of the reservoir size as the most

successful elementary rules to produce comparable results. This reduction in reservoir size equals a saving in power and time when operating the reservoirs.

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