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Parallel Programming in Spiking Neural P Systems with Anti-Spikes

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Abstract. In spiking neural P systems with anti-spikes, integers can be represented as the number of spikes/anti-spikes present in a neuron. Thus it is possible to represent increment, decrement, relational operations and assignment statements using spiking neural P systems. With these basic structures, it is also possible to represent programming language constructs like conditional, iterative and different types of execution constructs. In this paper we consider a general-purpose parallel programming language that handles integer variables and is implemented using spiking neural P systems with anti-spikes.

Key-words: spiking neural P systems with anti-spikes, Occam, simulation.

1. Introduction

Spiking neural P systems (in short, SN P systems) [4] are computational models inspired by the spiking activity of neurons in the brain. An SN P system is represented as a directed graph where nodes correspond to the neurons having spiking and forgetting rules. The rules involve the spikes present in the neuron in the form of occurrences of a symbol a. SN P systems operate in a locally sequential and globally maximal manner using a global clock. That is, in each neuron, at each step, if more than one rule is enabled, then only one of them is applied non-deterministically. All neurons fire in parallel at the system level. An SN P system is used as a computing device in various ways – acceptor, transducer and generator.

Spiking neural P systems with anti-spikes (in short, SN PA system) [7] work in the same way as standard SN P systems but deal with two types of objects called spikes

(a) and anti-spikes ($\overline{a}$). There is also a highest priority annihilation rule ($a\overline{a} \rightarrow \lambda$) that is implicitly present in each neuron of an SN PA system. Because of the use of two types of objects, the system can encode binary digits in a natural way and hence can represent the formal models more efficiently and naturally than the SN P systems. The power of SN PA systems as language generators is studied in [5]. In [6], the SN PA systems in transducer mode are used to simulate Boolean circuits. Here we demonstrate that SN PA systems are not only efficient in implementing hardware components but also software components like programming language constructs.

Both spiking neural P systems and artificial spiking neural networks are computational devices inspired by the concept of spiking neurons. There are several relations between these systems. For example, an SN P model for Hebbian learning using concepts borrowed from neuroscience and artificial neural network theory is presented in [3]. The present paper borrows some concepts present in [1], where spiking neural networks are used to represent variables and different constructs of a parallel programming language. In this paper we try to simulate the programming language constructs like *if*, *while*, *seq*, *par* and *alt* using SN PA systems.

This paper is organised as follows. We start with Section 2 by giving a brief introduction to the SN P systems with anti-spikes. In Section 3, we describe a very weak version of Occam and the language constructs considered for implementation. Occam is a parallel programming language used in the development of the VLSI chip called *transputer* that can execute concurrent processes [2]. The representation of integer variables, increment, decrement operations and assignment statements are considered in Section 4. In Section 5, we implement all considered programming language constructs.

2. Spiking Neural P System with Anti-Spikes

We briefly introduce the SN PA systems used in this paper.

Definition 2.1 A spiking neural P system with anti-spikes, of degree $m \geq 1$, is a construct

$$\Pi=(O,\ \sigma_1,\ \sigma_2,\ \sigma_3\ ,\ \ldots,\ \sigma_m\ ,\ syn\ ,\ IN,\ OUT),\ \text{where}$$

1. $O = \{\ a, \overline{a}\ \}$ is a binary alphabet. a is called *spike* and $\overline{a}$ is called an *anti-spike*.
2. σ_1, σ_2, σ_3 ,. . ., σ_m are neurons, of the form

$$\sigma_i=(n_i,\ R_i)\ ,\ 1 \leq i \leq m,\ \text{where}$$

   (a) n_i is the number of spikes or anti-spikes contained in the neuron σ_i and if $n_i > 0$ then the neuron is having n_i spikes and if $n_i < 0$ then the neuron is having n_i anti-spikes;

   (b) R_i is a finite set of *rules* of the form $E/b^r \rightarrow d^p$ where $b, d \in \{a, \overline{a}\}$, $r \geq 1$, $p \geq 0$, with the restriction that $r \geq p$ and E is either a regular expression over a or a regular expression over $\overline{a}$;

Like in [7], we avoid using rules $\overline{a}^r \to \overline{a}^p$, but not the other three types, corresponding to the pairs (a, a), $(a, \overline{a})$, $(\overline{a}, a)$.

3. $syn \subseteq \{1, 2, 3, \ldots, m\} \times \{1, 2, 3, \ldots, m\}$ with $(i, i) \notin syn$ for $1 \leq i \leq m$ (*synapses* among cells);
4. IN, $OUT \subseteq \{1, 2, 3, \ldots, m\}$ are the set of input and output neurons respectively.

A rule $E/b^r \to d^p$ is applied as follows. If the neuron σ_i contains k spikes when $b = a$ (or k anti-spikes when $b = \overline{a}$), and $b^k \in L(E)$, $k \geq r$, then the rule can *fire*, and upon application, r spikes (or anti-spikes) are consumed (thus only $k - r$ remain in σ_i) and p spikes (or anti-spikes) are released when $d = a$ (or $d = \overline{a}$), which will immediately exit the neuron. The spikes (or anti-spikes) emitted by the neuron σ_i will pass immediately to all neurons σ_j such that $(i, j) \in syn$. That means transmission of spikes/anti-spikes takes no waiting time (since the rules do not specify a time delay), the spikes/anti-spikes will be available in neuron σ_j in the next step. There is an additional restriction that a and $\overline{a}$ cannot stay together, they annihilate each other. If a neuron has either objects a or objects $\overline{a}$, and further objects of either type (maybe both) arrive from other neurons, such that we end with a^q and $\overline{a}^s$ inside, then immediately an annihilation rule $a\overline{a} \to \lambda$ (which is implicit in each neuron), is applied in a maximal manner, so that either a^{q-s} or $(\overline{a})^{s-q}$ remain for the next step, provided that $q \geq s$ or $s \geq q$, respectively. This mutual annihilation of spikes and anti-spikes takes no waiting time and the annihilation rule has priority over spiking and forgetting rules, so each neuron always contains either only spikes or anti-spikes. If we have a rule $E/b^r \to d^p$ with $L(E) = \{b^r\}$, then we write it in the simplified form as $b^r \to d^p$. If $p = 0$ in $E/b^r \to d^p$, then we write as $E/b^r \to \lambda$, where λ represents the empty string. These rules are similar to the forgetting rules of the standard SN P system, but here the forgetting rules also have regular expressions associated with them.

The *configuration* of the system is described by $\mathcal{C} = \langle \beta_1, \beta_2, \ldots, \beta_m \rangle$, where β_i is the number of spikes/anti-spikes present in neuron σ_i. The initial configuration is $\mathcal{C}_0 = \langle n_1, n_2, \ldots, n_m \rangle$.

A global clock is assumed and in each time unit, each neuron which can use a rule should do it (the system is synchronized), but the work of the system is sequential locally: only (at most) one rule is used in each neuron. For example, if a neuron σ_i has two firing rules, $E_1/{b_1}^{r_1} \to {d_1}^{p_1}$ and $E_2/{b_2}^{r_2} \to {d_2}^{p_2}$ with $L(E_1) \cap L(E_2) \neq \emptyset$, then it is possible that each of the two rules can be applied, and in that case only one of them is chosen non-deterministically. Thus, the rules are used in the sequential manner in each neuron, but neurons function in parallel with each other. In each step, all neurons which can use a rule of any type, spiking or forgetting, have to evolve, using a rule.

Using the rules in this way, we pass from one configuration of the system to another configuration; such a step is called a transition. For two configurations $\mathcal{C}$ and $\mathcal{C}'$ of Π we denote by $\mathcal{C} \Longrightarrow \mathcal{C}'$, if there is a direct transition from $\mathcal{C}$ to $\mathcal{C}'$ in Π.

A computation of Π is a finite or infinite sequence of transitions starting from the initial configuration, and every configuration appearing in such a sequence is called reachable. A computation halts if it reaches a configuration where no rule can be used. An SN PA system can be used as a computing device in various ways. In the generative mode, one of the neuron is considered as output neuron and it sends output to the environment. The moments of time when a spike is emitted by the output neuron are marked with 1, the moments of time when an anti-spike emitted is marked with 0 and no output moments are just ignored. This binary sequence is called the spike train of the system- it might be infinite if the computation does not stop. With halting configurations, we associate the language generated by the system as the set of binary sequence describing the spike trains.

If we consider both input and output neurons, then the SN PA system works as a transducer. In this paper we consider SN PA systems working in transducer mode.

3. A Simple Parallel Programming Language

The language described below is a very weak version of Occam handling only integer variables, and all variables are global. The language considered is similar to the one in [1].

We will use strings of characters starting with upper case letters as variables for integers.

The language consists of the following statements.

1. If X is a variable, then $X := 0$, $X := X + 1$, and $X := X - 1$ are statements. We will say that two statements are independent if no variable which may be used in one statement is referred to in the other.
2. If X and Y are variables, then $Y := X$ and $Y := -X$ are statements. They are called assignment statements.
3. If X is a variable, then $X = 0$, $X \neq 0$ and $X > 0$ are the tests.
4. If T is a test, and P and Q are statements, then $if\ T\ then\ P\ else\ Q$ is a statement.
5. If T is a test and P is a statement, then $while\ (T)\ P$ is a statement.
6. If $P_1, P_2, \ldots, P_n$ are statements, then $seq\{P_1; P_2; \ldots; P_n;\}$ is a statement.
7. If $P_1, P_2, \ldots, P_n$ are independent statements, then $par\{P_1; P_2; \ldots; P_n;\}$, and $alt\{P_1; P_2; \ldots; P_n;\}$ are statements.

Statements in this language have a natural denotational semantics, defined as follows. We define a valuation to be an assignment of integral values to some subset of the variables. Then each statement denotes a possibly non-deterministic, possibly non terminating, transformation from one valuation to another.

These denotations can be defined by structural recursion on the statements, as usual. So, for example, the transformation denoted by $par\{P_1; P_2; \ldots; P_n;\}$ is obtained by running the transformations denoted by $P_1, P_2, \ldots, P_n$ in parallel, and it only terminates when all of them terminate. On the other hand, the transformation denoted

by $alt\{P_1; P_2; \ldots; P_n;\}$ is obtained by running all of the denoted transformations in parallel, and it terminates just when one of its constituents terminates, the choice being non-deterministic if several of them terminate.
We show in the next section how the transformations denoted by the statements in this programming language can be implemented in spiking neural P systems with anti-spikes.

4. Representation of Variables and Implementation of Various Operators

Each variable X is represented using neuron σ_X. We use a representation where variable X has a non negative value n if the corresponding neuron σ_X has $2n$ spikes, X has a value $-n$ if it has $2n$ anti-spikes and $X = 0$ if σ_X has no spikes/anti-spikes. The four spiking rules in σ_X, $a(aa)^+/a^2 \to \overline{a}^2$, $\overline{a}(\overline{a}\overline{a})^+/\overline{a}^2 \to a^2$, $a \to \overline{a}$ and $\overline{a} \to a$ are used to read the value of X. These rules are fired when there is an odd number of spikes/anti-spikes in σ_X.

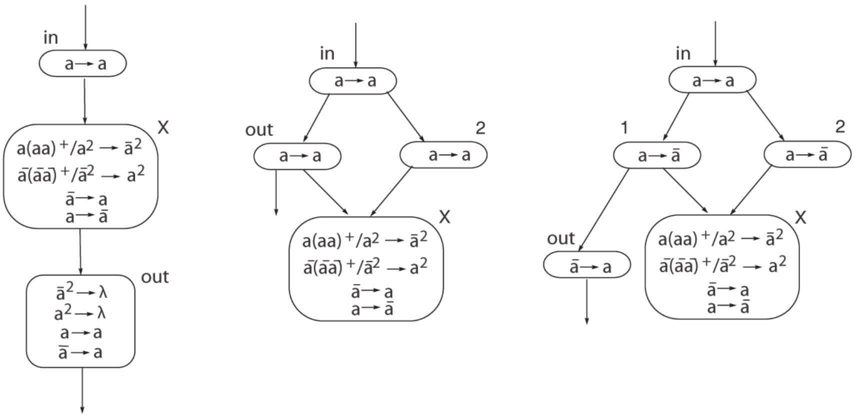
The neuron σ_X is fired when a spike or an anti-spike is sent in. If the variable X has a positive value say n, then the number of spikes present in X will be $2n$. When σ_X is activated by sending a spike, the number of spikes in σ_X becomes odd. So the rule $a(aa)^+/a^2 \to \overline{a}^2$ is used until it is left with a spike. Then it uses the rule $a \to \overline{a}$ to clear its contents. In a similar way, rules $\overline{a}(\overline{a}\overline{a})^+/\overline{a}^2 \to a^2$ and $\overline{a} \to a$ are used when X has a negative value.

The SN PA system for each statement or construct will have a group of spiking neurons. To implement the constructs in a uniform way, the SN PA system is triggered by a spike arriving to an input neuron σ_{in} and upon completion it activates some termination neuron σ_{out}, which passes the control to the next statement in the program.

Assigning a zero value to the variable X means clearing the contents of the neuron σ_X. The implementation is presented in Fig. 1(a). It is done through sending a spike to the neuron σ_X. The number of spikes/anti-spikes in σ_X becomes odd, so the rules are applied until all spikes/anti-spikes in σ_X are cleared. The output neuron sends a spike when σ_X becomes empty. A constant value can be assigned to the variable X by first clearing its contents and bringing a number of spikes/anti-spikes equal to twice the constant value.

4.1. Implementation of Increment and Decrement Statements

Incrementing the variable X will mean adding two spikes to neuron σ_X and decrementing the variable X will mean adding two anti-spikes to neuron σ_X. The implementations of increment and decrement operations are shown in Fig. 1(b) and Fig. 1(c) respectively. In each case after completion, the output neuron sends a spike to the next system.

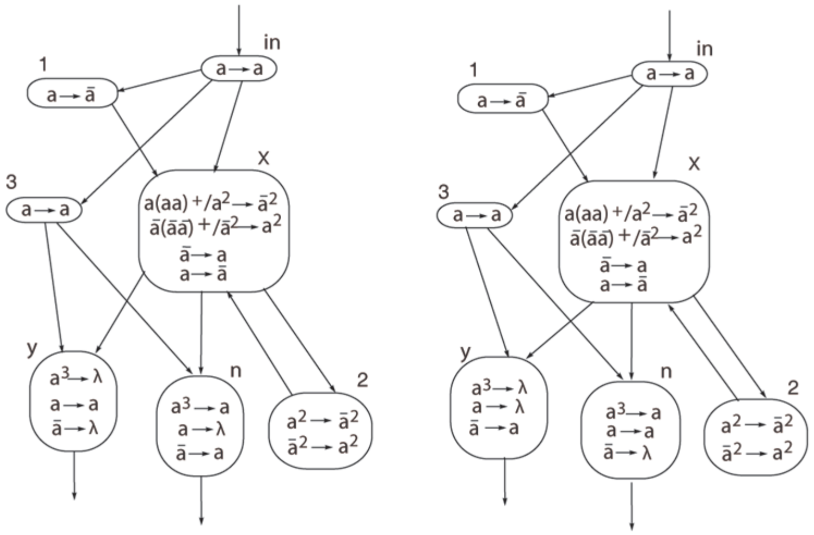


(a) X:=0 (b) X:=X+1 (c) X:=X-1

Fig. 1. Implementation of increment and decrement statements.

4.2. Implementation of Testing Statements

The test $X = 0$ is implemented with the SN PA system Π_T in Fig. 2(a), with one input neuron and two output neurons. The output neuron σ_y is fired if the test is true and output neuron σ_n is fired if the test is false. In the first step, the input neuron outputs a spike after it receives a spike from the previous system. The spike is sent to σ_1, σ_3 and σ_X. Now, we consider all the three cases.



(a) Test X=0 (b) Test X > 0

Fig. 2. Implementation of testing statements.

1. If $X = 0$, then the neuron σ_X is initially empty. After the arrival of a spike from the input neuron, neurons σ_1, σ_3 and σ_X will have a spike. In the second step, neurons σ_1 and σ_X use their rule $a \to \overline{a}$ and σ_3 uses its rule $a \to a$. The anti-spike from σ_X and the spike from σ_3 are annihilated in both the neurons σ_y and σ_n. Neuron σ_2 will have an anti-spike. σ_X receives an anti-spike from σ_1. In the third step σ_X uses its rule $\overline{a} \to a$ and sends a spike to σ_2, σ_y and σ_n. σ_2 uses its annihilation rule after it receives a spike from σ_X. In the last step, σ_n forgets its spike and σ_y spikes by using its rule $a \to a$, which means that the test is true.

2. If $X > 0$, say n, then the neuron σ_X contains an even number of spikes. After the arrival of a spike from the input neuron, neurons σ_1 and σ_3 have a spike in each and σ_X has odd number $(2n + 1 \geq 3)$ of spikes. σ_X fires in the second step using its rule $a(aa)^+/a^2 \to \overline{a}^2$ leaving $2n - 1$ spikes. The two anti-spikes are sent to σ_2, σ_y and σ_n. In the same step σ_1 fires by sending an anti-spike to σ_X and σ_3 fires by sending a spike to σ_y and σ_n. Now the neuron σ_X has even number $(2n-2 \geq 0)$ of spikes since it receives an anti-spike from σ_1. After the annihilation, both σ_y and σ_n will have an anti-spike. In the third step, σ_X will not spike while σ_2, σ_y and σ_n use their rules $\overline{a}^2 \to a^2$, $\overline{a} \to \lambda$ and $\overline{a} \to a$ respectively. At the end, σ_X is left with $2n$ spikes and σ_n spikes, which means that the test $X = 0$ is false.

3. If $X < 0$, say $-n$, then the neuron σ_X contains an even number of anti-spikes. After the arrival of a spike from the input neuron, neurons σ_1 and σ_3 have a spike in each and σ_X has odd number $(2n-1 \geq 1)$ of anti-spikes. Depending on the number of anti-spikes it has, neuron σ_X fires in the second step using one of its rules $\overline{a}(\overline{a}\overline{a})^+/\overline{a}^2 \to a^2$ or $\overline{a} \to a$ and remains with $(2n - 3) \geq 1$ or zero anti-spikes respectively. In the same step σ_1 fires and sends an anti-spike to σ_X while σ_3 fires and sends a spike to σ_y and σ_n. If σ_X uses its rules $\overline{a}(\overline{a}\overline{a})^+/\overline{a}^2 \to a^2$ in step 2 (when $X \leq -2$), then it sends two spikes to σ_2, σ_y and σ_n. After the second step, neuron σ_X has even number $(2n - 2 \geq 2)$ of anti-spikes and do not spike in the next step. Neurons σ_2, σ_y and σ_n use their rules $\overline{a}^2 \to a^2$, $a^3 \to \lambda$ and $a^3 \to a$ respectively in the third step to indicate that the condition is false. If σ_X uses its rules $\overline{a} \to a$ in step 2, then it sends a spike to σ_2, σ_y and σ_n. After the second step, neurons σ_2 has a spike and both σ_y and σ_n will have two spikes each and σ_X has an anti-spike. In the third step σ_X fires using its rule $\overline{a} \to a$ and sends a spike to σ_2, σ_y and σ_n. Neurons σ_2, σ_y and σ_n use their rules $\overline{a}^2 \to a^2$, $a^3 \to \lambda$ and $a^3 \to a$ respectively in the fourth step. In both cases, at the end, σ_X is left with $2n$ anti-spikes and σ_n spikes by using its rule $a^3 \to a$, which means that the test $X = 0$ is false.

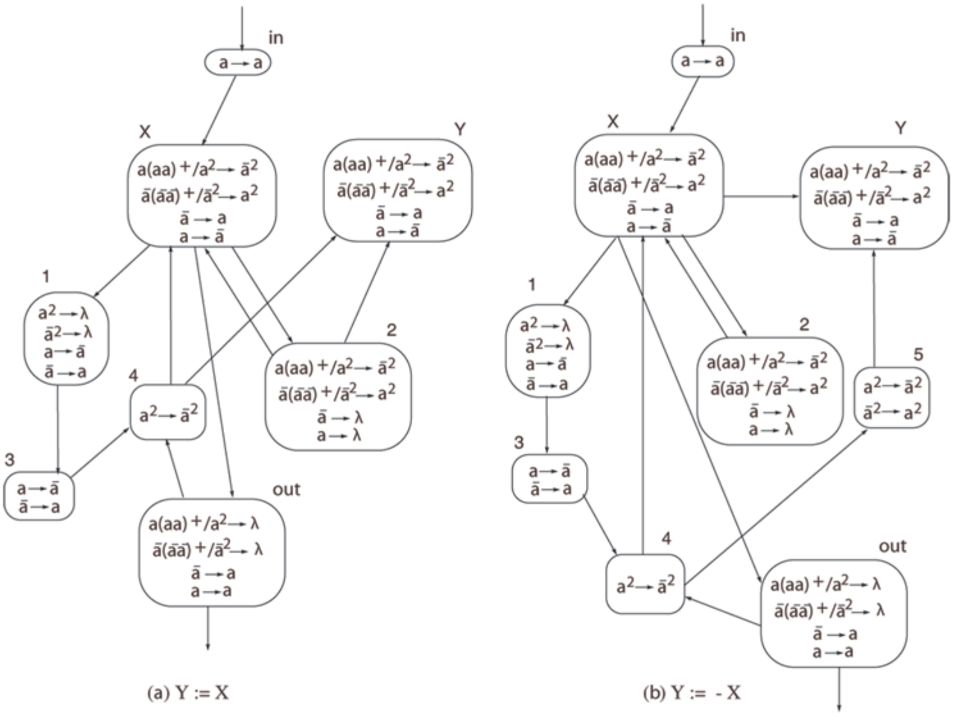
In all the three cases, after reading the contents of σ_X, it is restored to its original value.

To simulate the test $X \neq 0$, we simply swap the neurons σ_y and σ_n in Fig. 2(a). The SN PA system for the test $X > 0$ is shown in Fig. 2(b). We can observe from case. 2 above that when $X > 0$, after the step 2, σ_y and σ_n are left with an anti-spike.

In step 3, σ_n forgets the anti-spike whereas σ_y fires using its rule $\overline{a} \to a$, which means that the test $X > 0$ is true.

4.3. Implementation of Assignment Statements

The implementation of the assignment statement $Y := X$ is shown in Fig. 3(a). The neurons σ_X and σ_Y correspond to the variables X and Y respectively. The contents of the neuron σ_Y are cleared before the first step of the implementation. In step one, the input neuron sends a spike to the neuron σ_X. The number of spikes/anti-spikes in σ_X becomes odd. Now we again consider all the three cases.



(a) Y := X

(b) Y := - X

Fig. 3. Implementation of assignment statements.

When $X = 0$, σ_X is empty. When a spike arrives from the input neuron, there will be a spike in σ_X, so it uses the rule $a \to \overline{a}$ and sends an anti-spike to σ_1, σ_2 and the output neuron σ_{out}. The anti-spike is converted into spike inside the neurons σ_1 and σ_{out}. The anti-spike is ignored in σ_2. The spike from σ_1 is sent to σ_3. Neuron σ_3 converts the spike into anti-spike and sends it to σ_4. The output neuron sends a spike to σ_4 and the next construct. In σ_4, the spike and anti-spike are annihilated. At the end of simulation, both the neurons σ_X and σ_Y remain empty, representing that $X := 0$ and $Y := 0$.

When $X < 0$, say $X = -n$, then σ_X has $2n$ anti-spikes. When a spike arrives to σ_X, it will have an odd number $(2n-1)$ of anti-spikes. It uses the rule $\overline{a}(\overline{a}\overline{a})^+/\overline{a}^2 \to a^2$ and sends two spikes to neurons σ_1, σ_2 and σ_{out}. The two spikes are ignored in σ_1, as two spikes are stored in σ_2 and σ_{out}. The process continues until σ_X is left with an anti-spike (which means $2n-2$ anti-spikes are sent), then it uses $\overline{a} \to a$ and sends a spike to σ_1, σ_2 and σ_{out}. The spike from σ_1 is converted to anti-spike and sent to σ_3. Neuron σ_3 converts anti-spike to a spike and sends this spike to neuron σ_4. Here σ_2 and σ_{out} will have an odd number of spikes. In the next $n-1$ steps, σ_2 converts two of its spikes into anti-spikes and sends them to σ_X and σ_Y, where as σ_{out} ignores the two spikes. After these $n-1$ steps, σ_2 and σ_{out} are left with a spike. σ_2 ignores its spike where as output neuron sends a spike to σ_4 and to the next construct. Neuron σ_4 will have two spikes and use its rule $a^2 \to \overline{a}^2$ sending two anti-spikes to both σ_X and σ_Y. We can observe that at the end, σ_X and σ_Y will have $2n$ anti-spikes which means that the contents of X are copied into Y.

When $X > 0$, say $X = n$, when a spike arrives to σ_X, it will have an odd number $(2n+1)$ of spikes. The system works in the same way as above to copy the contents of σ_X into σ_Y, and the extra spike in σ_X gets annihilated in neuron σ_4.

The implementation of the statement $X := -Y$ is similar to $X := Y$ with an extra neuron σ_5 to complement the output of σ_2 and σ_4 before copying it into σ_Y.

5. *if*, *while*, *seq*, *par* and *alt* Constructions

We have the implementations for variables, assignment statements and relational statements. Using the combinations of these implementations, it is possible to implement the basic constructions of the programming language described above.

5.1. The *if* constructor

The statement *if T then P else Q* is implemented through the SN PA system Π_{if}. It contains three subsystems Π_T, Π_P and Π_Q. Π_P and Π_Q are the subsystems corresponding to the statements P and Q respectively.

Π_T is a structure of spiking neurons which represents the condition T of the *if* statement which must be satisfied if P is to be activated. When the output neuron of the previous construct fires it sends an input spike to the σ_{in} of Π_T. Whether or not the condition is satisfied will determine which output neuron of Π_T fires. If T is satisfied neuron σ_y is activated, and it will send a spike to the initiating neuron of the subsystem Π_P that, upon completion will activate the output neuron of the constructor *if*. If T is not satisfied then neuron σ_n is activated and it will send a spike to the initiating neuron of the subsystem Π_Q. Again upon completion of the subsystem Π_Q, the output neuron of the constructor *if* will be activated. In either case, Π_{if} halts after firing of its output neuron. The implementation of *if* statement is shown in Fig. 4.

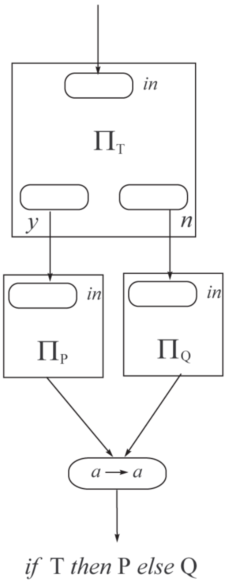


Fig. 4. Implementation of the *if* Statement.

5.2. The *while* Constructor

The *while* statement, *while* (T) P is implemented in a similar way as the *if* statement. Π_w is the SN PA system for the while statement. The *while* constructor must first check if a condition T is satisfied and then, if it is, allows a process P to be activated. The cycle continues until the condition represented by T is no longer met. If at any point T is not met when tested, then the *while* constructor passes control to the next process. The implementation of *while* statement is shown in Fig. 5.

Again T is the condition of the *while* statement, P is the process to be executed while this condition is satisfied. Neuron σ_{in} is a neuron that triggers the execution of a process. A spike emitted by σ_{in} will activate σ_w. Upon completion Π_P emits a spike to the input neuron of Π_w. If the condition T is met then neuron σ_y is activated, otherwise neuron σ_n is activated.

Neuron σ_y is connected to the input neuron of the process P. If neuron σ_n is triggered it will activate the output neuron of σ_w, passing the control to the next constructor.

5.3. The *seq* Constructor

The function of the *seq* constructor is to allow a series of processes to activate sequentially, with the next process in the list only being activated once the current process is completed.

Neuron σ_{in} is the activation neuron of the constructor. $P_1, P_2 \ldots, P_n$ is the sequence of processes to be activated and are implemented by disjoint subsystems; one subsystem for each process. Only after each process is completed, then it will send an activation spike to the next process in the sequence. As Fig. 6(a) shows, σ_{in} sends an activation spike to Π_{P_1}, which in turn sends an activation spike to Π_{P_2}, which sends an activation spike to Π_{P_3}, which upon its completion will send a spike that activates the next constructor.

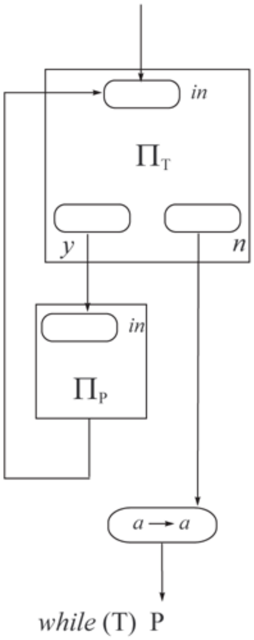
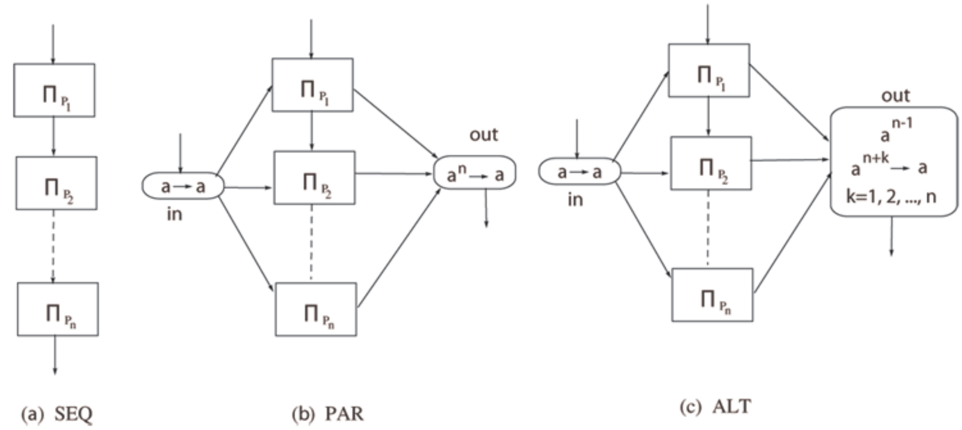


Fig. 5. Implementation of the *while* Statement.



(a) SEQ (b) PAR (c) ALT

Fig. 6. Implementation of *seq*, *par* and *alt* constructors.

5.4. The *par* Constructor

The *par* constructor activates a list of processes concurrently. As in Section 5.3, these are implemented by disjoint subsystems; one subsystem for each process. Control only passes from a *par* constructor once all of the listed processes have been completed.

Once again σ_{in} is the activation neuron of the constructor. When σ_{in} spikes, the spike gets transmitted to the input of each of the processes to be activated. As each process completes it will send a spike to σ_{out}, see Fig. 6(b). When all processes are completed, neuron σ_{out} accumulates n spikes and fires using the rule $a^n \to a$, which passes the control to the next constructor.

5.5. The *alt* Constructor

The *alt* constructor (essentially non-deterministic choice) is given a set of processes implemented on disjoint subsystems, runs them concurrently, and terminates when one of the processes terminates. So the initiating neuron of the *alt* sends an initiating spike to all of the initiating neurons of its constituent processes, and a spike from output neuron of any of the constituent processes is sufficient to trigger a spike from the terminating neuron of the *alt*. The implementation is shown in Fig. 6(c).

6. Conclusion

In this paper we have represented variables, several operations and different programming language constructs using spiking neural P systems with anti-spikes. The discussion above and the implementations we have done with spiking neural P systems with anti-spikes suggest the possibility of a compiler which takes a statement in a simple parallel programming language and constructs an SN PA system which can execute the computational meaning of the statement. One limitation of our implementation is that the neuron for a variable is to be replicated everywhere it is used with new outgoing synapses and new post-synaptic neurons. One important open problem is to find the implementation of the constructs in such a way that neurons representing the variables can have the same pre and post synaptic neurons and any kind of operation can be performed with those neurons without replicating them. The use of other variants of SN P systems to simulate the parallel programming constructs can also be a scope of further research.

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