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Representation of Gene Regulation Network by Hypothesis Logic Based Boolean Systems

Pierre Siegel¹, Andrei Doncescu^{2*}, Vincent Risch¹
and Sylvain Sené¹

¹LIS, UMR CNRS 7020, University of Marseille, 163 Avenue de
Luminy, Marseille, 13288, France.

^{2*}CNRS, LAAS, Univ de Toulouse, French West Indies
University-LAMIA, 7 Avenue du Colonel Roche, Toulouse,
F-31400, France.

*Corresponding author(s). E-mail(s): andrei.doncescu@laas.fr;
Contributing authors: pierre.siegel@lis-lab.fr;
vincent.risch@lis-lab.fr; sylvain.sene@lis-lab.fr;

Abstract

Boolean Dynamical Systems(*BDS*) are networks described by Boolean variables. A new representations of *BDS* is presented in this article by using modal non-monotonic logic (\mathcal{H}). This approach allows Boolean Networks to be represented by a set of modal formulas and **therefore can be used to describe and learn their properties.** The study of a *BDS* focuses in particular on the search of stable configurations, limit cycles and unstable cycles, which help to characterize a large type of Gene Networks. In this article is presented the identification of stable configurations, limit cycles and unstable cycles by introduction of a new concept, *ghost extensions*. Using *ghost extensions*, it is possible to translate *BDS*s in propositional calculus and consequently to use SAT algorithms. **SAT is very important because it is NP-Complete.**

Keywords: Genetic Networks, Computational Systems Biology, Boolean networks, Non-monotonic logic, Modal logic, Hypothesis logic, SAT algorithms

1 Introduction

Biological systems can be represented by a set of interacting elements (genes, proteins, enzymes, ...), whose states change over time. For genetic networks, the knowledge is regularly incomplete, uncertain and sometimes contradictory. It is therefore necessary to represent incomplete and revisable information. This representation has been studied in Artificial Intelligence since the late 1970s, especially by using non-monotonic logics and techniques derived from constraint programming. Default Logic \mathcal{DL} [9, 29] and Answer Set Programming ASP [23] have been used to study genetic networks [19, 43].

In these approaches, a set of genes is associated to a set of Boolean functions, updated over discrete time and view as Boolean Dynamical Systems(BDS). In the case of Genetic Networks Modeling, expression of a gene modulates other genes by activation/inhibition actions [2]. Gene Models based BDS had been used to find out feedback circuits theorems [12, 25, 30–35, 44], development biology [3, 11, 26], and physiology [8, 13, 24, 39].

The first formalism of BDSs as Logic Programs was introduced by Inoue [18] using monotonic logic, which is a limitation from biological knowledge representation viewpoint. In this article a formal links between Boolean Dynamical Systems (BDSs) and a modal non-monotonic logic called *hypothesis logic* (\mathcal{H}) [38, 41] is presented. Using a set of \mathcal{H} modal formulas, it is possible to obtain a new knowledge representation for BDSs(*interaction graphs* and *asynchronous transition graphs*) by a set of *Kripke Models*. BDS analysis focuses on recognition of stable configurations (or fixed points) and stable/unstable cycles/oscillations. An important result presented in this paper is the proof that stable configurations and stable cycles are represented by sets of extensions: one *stable extension* and a set of *ghost extensions*. They are calculated using very simple and efficient SAT algorithms. SAT is NP-Complete, therefore solve it instead of any other problem in NP [28]. These algorithms allow to distinguish among stable/unstable states.

Moreover they can calculate all the states of BDS [18]. In our opinion it is an important development regarding Boolean Network aspects with possible applications to Gene Signaling Pathways.

This article is structured as follows: Section 2 reminds basic results about non-monotonic logic. Section 3 gives the main definitions and notations related to \mathcal{H} . Section 4 gives tracks to use SAT algorithms. Section 5 gives a representation of genetic networks into \mathcal{H} . Section 6 gives the definitions on BDS. Section 7 gives general fundamental results and applications in biology. Section 8, present a syntax and a semantic representations of BDSs in \mathcal{H} . Section 9, gives the theorems which prove that the asynchronous asymptotic behaviors such as stable configurations and stable attractors, as well as unstable attractors, are properly calculated.

2 Non-monotonic logics and Default Logic

Protein-protein interactions and genetic interactions are a form of causality in the sens of Artificial Intelligence [45]. Therefore, the modeling of these systems could be made by logical inferences. Representing biological systems using a logical formalism may seem valid. For example the interaction of an entity i with j suggests a close relation with what is called in logic *material implication*, denoted as \rightarrow . However, such a representation in monotonic logic is not adapted because it drives often to inconsistencies. Monotonicity is a property of inference rules that never prunes the set of conclusions with the increasing of knowledge. Whereas this property is crucial in mathematics, it is largely questionable regarding reasoning with incomplete or contradictory information. A way to manage this is to deal with a *non-monotonic formalism*, including \mathcal{DL} or \mathcal{ASP} , which is a more tractable restriction of \mathcal{DL} . Default Logic concerns standard formulas of first order logic, to which contextual inference rules called defaults are added in order to deal with revisable information. A *default* is a local inference rule $d = \frac{A:B}{C}$, whose application specifically depends on the formulas A, B, C which compound it. The intuitive meaning is: “If A holds, if B is coherent with what is known, then C holds”. The fact that a default can be triggered or not depending on the context further leads to a notion of *extensions* as max-consistent sets of formulas with respect to the trigger of the defaults used to get it. The underlying reasoning is non-monotonic because adding here new information may invalidate previously triggered defaults. A first remark is that some default theories may have no extensions: this expresses a form of deep inconsistency which renders computation more difficult. This possible lack of extensions in \mathcal{DL} has been fully studied in the context of hypothesis logic. As shown in [38, 41], \mathcal{DL} is a fragment of \mathcal{H} . In the latter logic, theories always have extensions among which some of them, called *ghost extensions*, have no counterpart in \mathcal{DL} . A second remark is that \mathcal{DL} only computes *stable extensions*, which can be a drawback for Biological Systems Analysis. here, the goal is to represent the *dynamics* and in particular the *cycles*. These cycles may represent real fundamental phenomena in living organisms such as the cell cycle [7, 22], circadian cycle [1, 36], or the cardiorespiratory rhythm [14].

3 Hypothesis Logic

Hypothesis logic \mathcal{H} is a bimodal logic [6] with two modal operators L and $[H]$ [38, 41]. If f is a formula, the intuitive meaning of Lf is *f is proved/stated*. The dual H of $[H]$ is defined as $Hf = \neg[H]\neg f$. The intuitive meaning of Hf is *f is a hypothesis*, and hence $[H]f$ means *$\neg f$ is not a hypothesis*. For example, a default $\frac{A:B}{C}$ can be interpreted/translated in \mathcal{H} by the modal formula $LA \wedge HB \rightarrow LC$ whose intuitive meaning is: If A is stated and B is a valid hypothesis then C is stated. This modal formula can also give translations of the Prolog clause and of the ASP rule: $C :- A, \text{not}(B)$.

4 Representation of Gene Regulation Network by Hypothesis Logic

The formalism used in this article uses a restricted definition of the language of \mathcal{H} , sufficient to represent BNs and Boolean genetic networks. This restriction also allows to translate \mathcal{H} into propositional calculus and to use SAT algorithms.

3.1 Syntax

The language of \mathcal{H} , denoted by $\mathcal{L}(\mathcal{H})$, is defined by the following inductive rules:

1. Any formula of propositional calculus \mathcal{PC} is in $\mathcal{L}(\mathcal{H})$.
2. The set of atoms (or propositional variables) of $\mathcal{L}(\mathcal{H})$ is finite.
3. Whenever f and g are formulas of \mathcal{PC} , Lf , $[H]f$, Hf , $\neg Lf$, $\neg[H]f$, $\neg Hf$ are in $\mathcal{L}(\mathcal{H})$ too¹.

And no other formulas are in $\mathcal{L}(\mathcal{H})$ than those formed by applying these two rules. Operator L has the properties of the modal system T [6] and $[H]$ has those of the modal system K [6]. As a consequence, the inference rules and axiom schemata of \mathcal{H} are:

1. All inference rules and axiom schemata of first-order logic.
2. (N[H]): $\vdash f \Rightarrow \vdash [H]f$, the *necessitation rule* for $[H]$.
3. (NL): $\vdash f \Rightarrow \vdash Lf$, the *necessitation rule* for L .
4. (K[H]): $\vdash [H](f \rightarrow g) \rightarrow ([H]f \rightarrow [H]g)$, the *distribution axiom schema* for $[H]$.
5. (KL): $\vdash L(f \rightarrow g) \rightarrow (Lf \rightarrow Lg)$, the *distribution axiom schema* for L .
6. (TL): $\vdash Lf \rightarrow f$, the *reflexivity axiom schema* for L .

Unlike L , the axiom of reflexivity does not hold for $[H]$. It is important to remark that there are so far no connections between L and $[H]$. We force this connection by adding the following *link axiom schema*:

$$(LI): \vdash \neg(Lf \wedge H\neg f).$$

This very weak axiom is the basis of \mathcal{H} . It means that it is impossible to prove f and to assume the hypothesis $\neg f$ at the same time. Note the following equivalences: $\neg(Lf \wedge H\neg f) \Leftrightarrow Lf \rightarrow \neg H\neg f \Leftrightarrow H\neg f \rightarrow \neg Lf$, where the second formula means that *if we prove f , we cannot assume the hypothesis $\neg f$* and the third formula means that *if we assume the hypothesis $\neg f$, we cannot prove f* .

3.2 Semantics

Kripke semantics [21] is defined for *normal modal logics* (i.e., the logics which contain at least axiom (K)). We remind here the bases needed for our developments. A *Kripke structure* is a digraph $K = (W, R)$ where the *universe* W is a set $\{w_1, \dots, w_n\}$ of *worlds* and the *accessibility relation* $R \subseteq W \times W$ is a binary relation among worlds. When $w_j R w_k$, w_k is *accessible* from w_j . A

¹The full definition of \mathcal{H} further states that any formula of first-order logic is in $\mathcal{L}(\mathcal{H})$, and that, whenever f and g are in $\mathcal{L}(\mathcal{H})$, $\neg f$, $(f \wedge g)$, $(f \vee g)$, $(f \rightarrow g)$, are in $\mathcal{L}(\mathcal{H})$ too.

Kripke model is obtained by assigning in every world a truth value to every atom i . This makes possible to assign a truth value to all the formulas of PC. A world is then mapped to a logical interpretation. Formulas other than those of PC are assigned to worlds with the following condition: for all f , Lf is true in a world w_k if and only if f is true in all accessible worlds from w_k . The different axioms that hold in different modal logics depend on the properties of the accessibility relations R . For the system K , R is any relation, while reflexivity axiom (TL) holds if and only if R is reflexive.

As shown in [38], \mathcal{H} has a Kripke semantics with two accessibility relations, $R[H]$ for $[H]$, RL for L . $R[H]$ is the relation of system K and RL is the relation of system T , hence reflexive. The relationship between the two relations, is given by the extra constraint $RL \subseteq R[H]$ which corresponds to the link axiom. Proofs of completeness, correctness, and compactness for \mathcal{H} are given in [38].

Remark. *The axiomatic of \mathcal{H} was defined to give an alternative minimum of axioms. With the full definition of \mathcal{H} , by adding axiom (4) $\vdash Lf \rightarrow LLf$. But, in so $LLf = Lf$ and this addition makes us lose the notion of dynamics necessary for representing a BDS and thus of its underlying genetic network. Indeed, to represent the dynamics we consider here that Lf represents an action (for example the production of a represented by a Kripke world w . All the accessible worlds from w are the following steps. and thus Lp by (TL), in all these accessible worlds, which, by induction would mean that p will be produced all In a biological framework and for dynamical systems, this We encounter the same type of problem when adding axiom (5)*

3.3 Hypothesis theories and extensions

As defined above, \mathcal{H} is a non-monotonic logic. In order to deal with the *revisable* character of usual informations, for example of biological nature, a notion of *extension* is added just as in DL. However, contrary to the latter, three kinds of extensions are considered here, namely stable extensions, ghost extensions and sub-extensions.

Definition 1 Given \mathcal{H} :

- A *hypothesis theory* is a pair $\mathcal{T} = \{HY, F\}$, where HY is a set of hypotheses and F is a set of formulas of \mathcal{H} .
- An *extension* E of \mathcal{T} is a set $E = Th(F \cup HY')$, such that HY' is a maximal subset of HY consistent with F .
- A *sub-extension* E of \mathcal{T} is a set $E = Th(F \cup HY')$, such that HY' is a non-maximal subset of HY consistent with F .
- E is a *stable extension* if it is an extension that satisfies the *coherence property*:

$$\forall Hf, \neg Hf \in E \implies L\neg f \in E.$$

Thanks to the link axiom schema, we hence get: $\forall f, L\neg f \in E \iff \neg Hf \in E$.

- E is a *ghost extension* if it is an extension that satisfies: $\exists Hf, \neg Hf \in E$ and $L\neg f \notin E$.

Thus, an extension is obtained by adding any of the largest consistent sets of hypotheses to F while remaining consistent. Intuitively, E is stable if whenever it is forbidden to assume the hypothesis f , $\neg f$ is proved. It is a ghost extension otherwise. Stable extensions correspond to the standard extensions of DL. Ghost extensions do not have any correspondence in DL nor in ASP. In [38, 41] it is proved that if F is consistent then $\mathcal{T} = \{\text{HY}, F\}$ has at least one extension, and that a default theory Δ can be translated into a hypothesis theory $\mathcal{T}(\Delta)$ such that the set of standard extensions of Δ is isomorphic to the set of stable extensions of $\mathcal{T}(\Delta)$.

The following definitions will help to characterize the stable configurations and the cycles of BDSs.

Definition 2 Let E be an extension.

- E is *complete* if, for all $i \in V$, $\text{Hi} \in E$ or $\text{H}\neg i \in E$.
- An $i \in V$ is *free* in E if $\text{Li} \notin E$ and $\text{L}\neg i \notin E$. It is *fixed* otherwise.
- The *degree of freedom* of E , denoted by $\text{degree}(E)$, is the number of free atoms that compose it.
- If the extension $E = \text{Th}(F(G) \cup \{\text{Hy}_k\})$, the *mirror* of E , denoted by $\text{mir}(E)$, is the set $\text{Th}(F(G) \cup \{\text{H}\neg y_k\})$.

4 Propositional algorithm

This section gives tracks to translate \mathcal{H} into propositional calculus (\mathcal{PC}) and to use SAT algorithms. Modal logics can be translated into first order logic by Skolemization methods. Then it is possible to use theorem provers based on the unification algorithm and the resolution principle. For example, it is possible to translate the modal operator L by a function fL of first order logic. But, by nesting the modalities, $LL\dots p$ is translated by $fL(fL(\dots(p)))$. The Herbrand universe (the set of ground formulas) is then infinite and therefore, the use of SAT algorithms is not appropriate.

On the contrary, with the restricted definition of \mathcal{H} used here, there is no nesting of modalities (no LLf , HLf , ...). So, all modal formulas are of the form Lf , where f is a PC formula. If the set of propositional variables (atoms) is finite, we can then consider that the Herbrand universe is finite which opens the way for using SAT algorithms.

Let us recall some definitions of \mathcal{PC} . A *literal* is an atom a , or the negation of an atom $\neg a$. A *disjunctive clause* (DC) is a disjunction of literals and, a *conjunctive clause* (CC) is a conjunction of literals. A *conjunctive normal form formula* (CNF formula) is a conjunction of one or more DCs. A *disjunctive normal form formula* (DNF formula) is a disjunction of one or more CCs. Every PC formula can be converted into an equivalent CNF formula and, also into an equivalent DNF formula.

Remember that for \mathcal{H} , the modal formulas are of the form Lp , Hp , or $[H]p$, where p is a \mathcal{PC} formula. In the following a modal formula is *elementary* if p

is a literal. Let F be a set a formulas of \mathcal{H} . We translate F into a set of \mathcal{PC} formulas. This translation is done in the following way:

Translation:

- 1) Any modal formula Lp of F is translated into $Lp' = L(c_1 \wedge \dots \wedge c_n)$, where p' is the CNF of p . All c_i are therefore disjunctive clauses.
- 2) Any modal formula Hq of F is translated into $Hq' = H(d_1 \vee \dots \vee d_m)$ where q' is the DNF of q . All d_i are therefore conjunctive clauses.
- 3) The axiomatics of normal modal logics allows us to prove that:
 - $L(p_1 \wedge \dots \wedge p_n) \equiv (Lp_1 \wedge \dots \wedge Lp_n)$.
 - $H(q_1 \vee \dots \vee q_n) \equiv (Hq_1 \vee \dots \vee Hq_n)$

We can therefore replace any formula $L(p_1 \wedge \dots \wedge p_n)$ by a set $\{Lp_1, \dots, Lp_n\}$ of disjunctive clauses and, any formula $H(p_1 \wedge \dots \wedge p_n)$ by a set $\{Hq_1, \dots, Hq_n\}$ of conjunctive clauses.

- 5) We can then use a *renaming* which consists in replacing a \mathcal{PC} formula by a new atom logically equivalent:

Any Lp_i (resp. Hq_j), such that p_i (resp. q_j) is not a literal, is replaced by a couple $\{Lx, x \equiv p_i\}$ (resp. by $\{Hy, y \equiv q_j\}$).

So F is replaced by a set of propositional formulas and elementary modal formulas. Note that it is also possible to translate each of these propositional formulas in its CNF form. ie a finite set of disjunctive clauses.

- 6) It remains to translate the set of elementary modal formulas into PC. This can be done by renaming each of these formulas by a new atom.
-

This translation is not enough for obtaining a SAT algorithm, because the axiomatic of \mathcal{H} is not given. It remains to translate it into \mathcal{PC} :

- The reflexivity axiom of $L : Lf \rightarrow f$
- The link axiom: $\neg(Lf \wedge H\neg)f$
- The distribution axiom for $L : \vdash L(f \rightarrow g) \rightarrow (Lf \rightarrow Lg)$,
- The distribution axiom for $[H] : \vdash [H]f \rightarrow g \rightarrow ([H]f \rightarrow [H]g)$.

Since the set of CNF if is finite, each of these axioms can be translated into a set of modal propositional formulas where f and g take as values all the formulas of this set. Then we rename all the CNF formulas by new equivalent propositions. All modal formulas are then elementary, and it is possible to represent each of them by an atom.

If $\mathcal{T} = \{HY, F\}$ is an hypothesis theory, the computation of all the extensions of \mathcal{T} is done by adding to the translation of F each translated subset of HY , and keeping only those among them that are the maximals consistent ones with F . This can be done by using a SAT algorithm. This solution exists, but it is, of course, not interesting because of the size of the translations.

Another possible solution would be to consider that each modality is a predicate of first order logic, and that axioms are first order formulas. For

example the link axiom $Lf \rightarrow \neg H\neg f$ is translated by $L(f) \rightarrow \neg H(\neg f)$, L and H being predicates. This translation is possible because there is no modality nesting ; moreover, the translation does not contain any functions. These formulas could be considered as global constraints which are used by the SAT algorithm when needed.

5 Representing genetic networks into \mathcal{H}

A *genetic network* represents interactions among genes or proteins in cell [3, 10, 11, 17, 20, 27]. From now on, let us consider that the entity at stake are proteins. In a context of modeling, a protein is classically represented by an integer $i \in \{1, \dots, n\}$. Its *concentration* is denoted by x_i . In such networks, given a protein i , a set of interactions (or influences) from a set of proteins toward i describes in which conditions the concentration of i evolves. In the most general case, a concentration x_i is a real number, difficult to measure. Here, we study the particular case where the concentrations x_i are in $\{0, 1\}$, which is legitimate for genetic networks [19].

Genetic networks can be studied with the formalism of BNs and their underlying BDSs, defined in the following section. Here, in order to introduce our representation, it is sufficient to know that, for a BDS, the concentration $x_i = 1$ (resp. $x_i = 0$) denotes the presence (resp. the absence) of protein i in the cell. To lighten the notations, we will identify a numbered Boolean variable x_i directly with i .

One of the interests of hypothesis logic is that this bi-modal logic enables us to use three kinds of information: i , Li and Hi . Hence, by combining modalities with negations, we can use $\{i, Hi, H\neg i, Li, L\neg i\}$. Remark that in \mathcal{H} , we have: $Li \neq \neg L\neg i$, $\neg Li \neq L\neg i$, $Hi \neq \neg H\neg i$ and $\neg Hi \neq H\neg i$. This increasing of expressiveness allows for a more precise representation of biological networks. Let us consider the genetic network of a cell, and i ones of its protein. We can then give the meanings of L and H in the context of genetic networks.

- i means that the protein i is present in the cell and $\neg i$ that it is absent.
- Li means that i is produced by the cell (i is being activated) and $\neg Li$ means that i is not produced (i is not being activated).
- $L\neg i$ means that i is destroyed by the cell (i is being inhibited) and $\neg L\neg i$ means that i is not destroyed (i is not being inhibited).
- Hi (resp. $\neg Hi$) means that the cell gives (resp. does not give) the permission to attempt to produce i . In other words, the cell has (resp. has not) the ability to activate i .
- $H\neg i$ (resp. $\neg H\neg i$) means that the cell gives (resp. does not give) the permission to attempt to destroy i . In other words, the cell has (resp. has not) the ability to inhibit i .

Regarding the use of \mathcal{H} in this context, the role of an extension appears to gather a maximum of consistent permissions. Note that even if Hi stands for the cell giving permission to attempt the production of i , this production is not mandatory. It can be carried out or not, according to the context (*i.e.*, the set

of all interactions in the cell). Similarly $H\neg i$ gives the authorization to destroy i . It is important to note that Li and $L\neg i$ are actually actions (production or destruction of a protein). So there is a difference between $L\neg i$ which says that i is destroyed, and $\neg Li$ which says that i is not produced, and hence is weaker. There is a similar distinction between $H\neg i$ and $\neg Hi$ (and between Li and $\neg L\neg i$; and between Hi and $\neg H\neg i$).

Remark. For a cell, the production/destruction occurs practically at time t . This temporal notion could call for the use of temporal logics [3]. In our approach, using \mathcal{H} , it is not necessary to use a specific modality for representing time, since it is implicitly included in the axiomatics of H , via the accessibility relation of Kripke semantics. As such, \mathcal{H} is adapted to the representation of the dynamics of change. In other words, \mathcal{H} allows to formalize time, without having to add an additional level of representation.

The proposition below gives some general properties of \mathcal{H} , particularly adequate for the modeling of the different states of proteins in a cell.

Proposition 1 *Given i a protein, the following results hold in \mathcal{H} :*

- (1) $Li \rightarrow i$ and $L\neg i \rightarrow \neg i$ (i.e., if i is produced (resp. destroyed), then i is present (resp. absent)).
- (2) $\neg(Li \wedge H\neg i)$ and $\neg(L\neg i \wedge Hi)$ (It is impossible to produce (resp. destroy) i and to give the permission to destroy (resp. produce) i it at the same time).
- (3) $\neg(Li \wedge L\neg i)$ (It is impossible to produce and destroy i at the same time).

Proof \mathcal{PC} and axioms of \mathcal{H} are all what is needed.

- (1) $Li \rightarrow i$ and $L\neg i \rightarrow \neg i$ are instances of axiom (T).
- (2) $\neg(Li \wedge H\neg i)$ and $\neg(L\neg i \wedge Hi)$ are instances of the linking axiom (LI).
- (3) $Li \rightarrow i$ and $L\neg i \rightarrow \neg i$ are two instances of (1). In \mathcal{PC} we have $(Li \rightarrow i) \rightarrow (\neg Li \vee i)$ and $(L\neg i \rightarrow \neg i) \rightarrow (\neg L\neg i \vee \neg i)$. Therefore we obtain $\neg Li \vee i$ and $\neg L\neg i \vee \neg i$ from which we derive, by resolution, $\neg Li \vee L\neg i \rightarrow \neg(Li \wedge L\neg i)$. ■

6 Boolean dynamical systems

A finite BDS describes an evolution of the interactions in a BN of a set $V = \{1, \dots, n\}$ of n entities numbered from 1 to n , over discrete time. A *configuration* $x = (x_1, \dots, x_n)$ of the network is an assignment of a truth value $x_i \in \{0, 1\}$ to each element i of V . The set of all configurations (i.e., all interpretations on the logic side), called the *configuration space*, is denoted by $X = \{0, 1\}^n$. A *dynamics* of such a network is modeled *via* both a function f , called the *transition function*, and an *updating mode* μ that defines how the elements of V are updated over time. More formally, $f : X \rightarrow X$ is such that $x = (x_1, \dots, x_n) \mapsto f(x) = (f_1(x), \dots, f_n(x))$, where each function $f_i : X \rightarrow \{0, 1\}$ is a *local transition function* that gives the evolution of i over time.

There is an uncountable number of updating modes². Among them, the parallel and the fully asynchronous ones remain the most used [19, 43]. The *parallel* updating mode is such that all the entities of the network are updated at each time step. Conversely, the *fully asynchronous* updating mode is a non-deterministic variation in which only one entity is updated at a time. In the sequel, we restrict our study to fully asynchronous dynamics [30, 33] which we will abbreviate by asynchronous dynamics for the sake of simplicity.

6.1 Asynchronous transition graphs

Let $X = \{0, 1\}^n$ be a configuration space and $f : X \rightarrow X$ a function that defines a BN. The *asynchronous dynamics* of f is given by its asynchronous transition graph (ATG) $\mathcal{G}(f) = (X, T(f))$, a digraph whose vertex set is the configuration space and arc set is the set of effective asynchronous transitions such that:

$$T(f) = \{(x, y) \in X^2 \mid \exists i \in V, x = (x_1, \dots, x_i, \dots, x_n), \\ y = (x_1, \dots, x_{i-1}, f_i(x), x_{i+1}, \dots, x_n), x \neq y\}.$$

Therefore, if $(x, y) \in T(f)$, x and y differ exactly by one element; the transition is *unitary*.

Remark. *By definition, we relate a unique ATG $\mathcal{G}(f)$ to a given Moreover, by construction of ATGs, $\mathcal{G}(f) = \mathcal{G}(g)$ and g are equivalent (i.e., $f(x) \equiv g(x)$ for every x), f and g have the same truth tables. A function, its truth tables and its ATG are therefore distinct the same object, the asynchronous dynamical system.*

An *orbit* in $\mathcal{G}(f)$ is a sequence of configurations (x^0, x^1, x^2, \dots) such that either $(x^t, x^{t+1}) \in T(f)$ or $x^{t+1} = x^t$ if $x^t = f(x^t)$ (i.e., x^t has no successors). A *cycle* of length r is a sequence of configurations (x^1, \dots, x^r, x^1) with $r \geq 2$ whose configurations x^1, \dots, x^r are all different. From this, we derive what is classically called an asynchronous attractor in dynamical systems. An *attractor* is terminal *strongly connected component* (SCC) of $\mathcal{G}(f)$, i.e., a SCC with no outward transitions. Among attractors, we distinguish stable configurations from stable cycles. A *stable configuration* is a trivial attractor, i.e., a configuration x such that $\forall i \in V, x_i = f_i(x)$, which implies that $x = f(x)$. A *stable cycle* is a cyclic attractor such that, in $\mathcal{G}(f)$, $\forall t < r, x^{t+1}$ is the unique successor of x^t and x^1 is the unique successor of x^r . If an attractor is neither trivial nor cyclic, it is called a *stable oscillation*. When it is possible to get out from a non trivial SCC, this SCC is called an *unstable cycle* or an *unstable oscillation* depending on whether it is cyclic or not. An orbit that reaches a stable configuration stays there endlessly. Similarly, when it reaches a stable cycle

²Uncountable because we can apply the Cantor's diagonal argument on the set of deterministic updating modes which are basically defined as infinite sequences of subsets of nodes of the network.

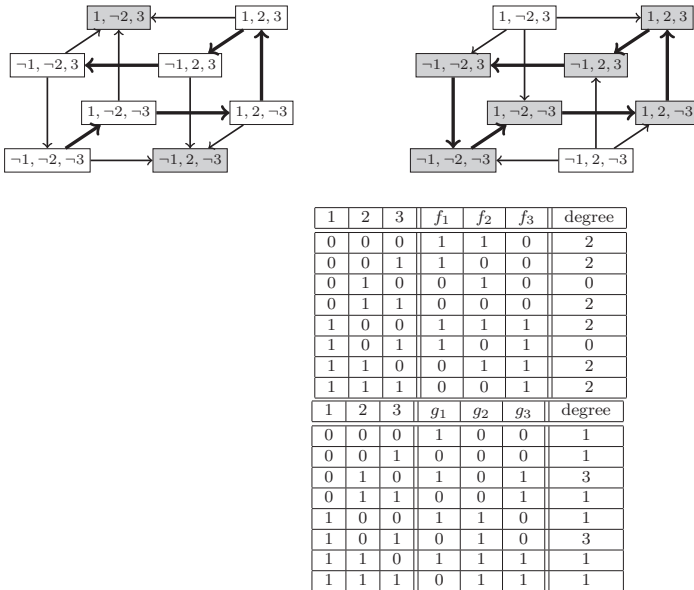


Fig. 1 ATGs and truth tables with degree of freedom, of functions (left) f , and (right) g presented in Example 1.

or a stable oscillation, it adopts endlessly a stable oscillating behavior. Notice that in the figures of this article, unless otherwise clearly specified recurring configurations, *i.e.*, configurations belonging to an attractor, are pictured in gray, and cycles are represented by bold transitions. Moreover, notice that the main difference between a stable cycle and an unstable one is that the first one represents a single orbit while the second one represents an infinity of orbits.

Example 1 Boolean positive and negative circuits of size 3:

Consider $V = \{1, 2, 3\}$, $x \in \{0, 1\}^3$ and two functions/BNs f and g such that $f(x_1, x_2, x_3) = (f_1(x), f_2(x), f_3(x)) = (\neg x_2, \neg x_3, x_1)$ and $g(x_1, x_2, x_3) = (g_1(x), g_2(x), g_3(x)) = (\neg x_3, x_1, x_2)$. From the definitions of f and g , it is possible to derive their related truth tables and ATGs, $\mathcal{G}(f)$ and $\mathcal{G}(g)$, pictured in Figure 1.

For these figures, the 8 rectangles are the vertices of the graph that represent the 2^3 possible assignments of $V = (1, 2, 3)$. A transition between 2 vertices corresponds to an arrow in these pictures. As the transition graph is asynchronous for each transition/arrow (x, y) , x differs from y by a single component. Therefore, there are up to 3 transitions leaving each configuration.

Here, $\mathcal{G}(f)$ has two symmetric stable configurations, $(-1, 2, -3)$ and $(1, -2, 3)$. These configurations are stable because no arrow comes out. The other six configurations induce a cycle, shown by the bold arrows. This cycle is unstable because it is possible to leave it, for example at vertex $(-1, -2, -3)$.

$\mathcal{G}(g)$ has a cycle of length 6, shown in bold. This cycle is stable because it does not have any outward transition.

12 Representation of Gene Regulation Network by Hypothesis Logic

We will prove in Section 8 that the two stable configurations of $\mathcal{G}(f)$ correspond to two stable extensions of \mathcal{H} , and that the stable cycle of $\mathcal{G}(g)$ corresponds to a set of 6 ghost extensions of degree 1.

The functions f and g can also be represented by *elementary circuits*, pictured in Figure 5. These ones are special cases of *interaction graphs*, defined below.

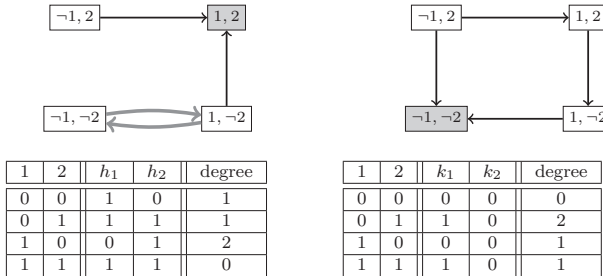


Fig. 2 ATG and truth table with degree of freedom of functions (left) h and (right) k presented in Example 2 and 3.

Remark. *In order to draw the ATG of function f , the easiest way is to use its truth table. For a line $l = (x_1, \dots, x_n, f_1(x), \dots, f_n(x))$ of the table, (x_1, \dots, x_n) is a vertex of the ATG and $(f_1(x), \dots, f_n(x))$ will allow to draw the arcs starting from this vertex: for any x_i of l such that $x_i \neq f_i(x)$ then the picture contains an arc that goes from the node $(x_1, \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_n)$ to the node $(x_1, \dots, x_{i-1}, f_i(x), x_{i+1}, \dots, x_n)$.*

Example 2 Consider the function $h(x_1, x_2) = (\neg x_1 \vee x_2, x_1 \vee x_2)$ pictured in Figure 2. This ATG has a stable state $(1, 2)$ and an unstable cycle $\{(-1, 2), (-1, -2)\}$. There is an infinity of possible orbits because one can follow the unstable cycle indefinitely, before attending randomly $(1, -2)$ and stabilizing in $(1, 2)$.

Example 3 Consider the function $k(x_1, x_2) = (x_2, x_1 \wedge \neg x_1 \wedge x_2)$, pictured in Figure 2. This ATG has a stable state $\{-1, -2\}$ and no cycles.

Example 4 (Boolean positive circuit of size 4) Consider the BDS of function $f_2(x_1, x_2, x_3, x_4) = (\neg x_4, x_1, \neg x_2, x_3)$, pictured in Figure 3. This BDS admits two stable configurations $(1, 2-3, -4)$ and $(-1, -2, 3, 4)$ pictured in gray, and an unstable oscillation, whose arcs are pictured in bold gray.

Example 5 (Boolean negative circuit of size 4) Consider the BDS of function $g_2(x_1, x_2, x_3, x_4) = (\neg x_4, x_1, x_2, x_3)$, pictured in Figure 4. This BDS admits one stable cycle of length 8, whose arcs are pictured in bold and one unstable cycle of length 8, whose arcs are pictured in bold gray.

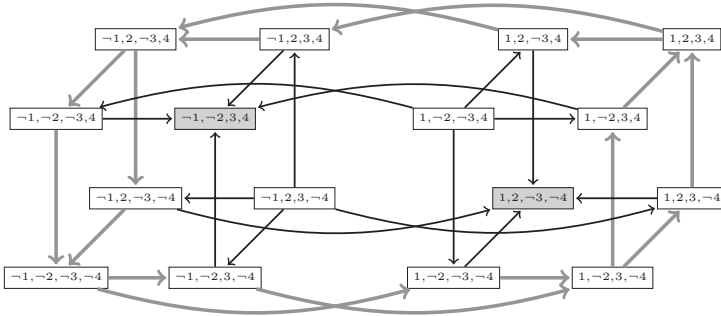


Fig. 3 ATG of the Boolean positive circuit of size 4 presented in Example 4.

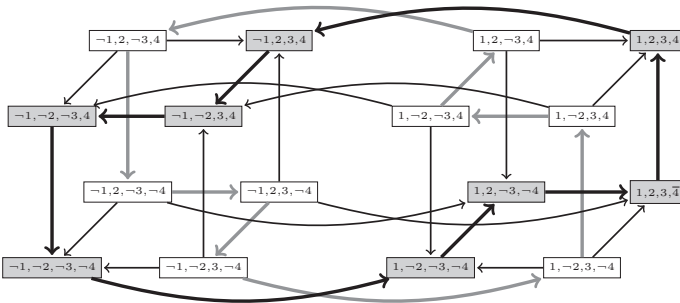


Fig. 4 ATG of the Boolean negative circuit of size 4 presented in Example 5.

6.2 Interaction graphs and circuits

An ATG is a very precise tool for studying the behavior of a function, but its size is exponential depending on the number of entities. Regarding practical applications, the information is often represented by more compact and more readable graphs of a different type, namely *interaction graphs* (IGs). This may be particularly the case for some biological data, which come from experiments that generally simply yield correlations among gene expressions.

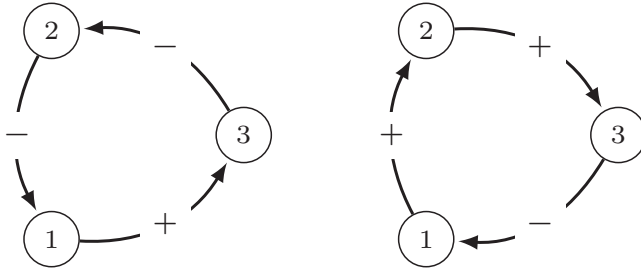


Fig. 5 (left) The IG (a positive circuit) associated with ATG $\mathcal{G}(f)$ and (right) the IG (a negative circuit) associated with ATG $\mathcal{G}(g)$, introduced in Example 1.

An IG is a signed digraph $G = (V, I)$, where $V = \{1, \dots, n\}$ is the vertex set corresponding to the so called entities, and $I \subseteq V \times S \times V$, with $S = \{-, +\}$ is the arc set corresponding to the so called interactions. An arc $(i, +, j)$ (resp. $(i, -, j)$) is said to be *positive* (resp. *negative*). From a dynamical point of view, the presence of an arc (i, s, j) in an IG means that the value of i affects the value of j , positively or negatively according to s : we say that i regulates j .

A circuit $C = \{(i_1, s_{(1,2)}, i_2), \dots, (i_k, s_{(k,1)}, i_1)\}$ of size k is *elementary* if all the i_s that compose it are distinct. A circuit is *positive* (resp. *negative*) if it contains an even (resp. an odd) number of negative arcs.

Consider the toy example where j has only one incoming arc from i . In this case, the effect of the regulation is obvious: if the arc is positive (resp. negative), j will take the value (resp. the opposite value) of i after one update. Remark that elementary circuits are regulated this way.

More generally, consider an IG that contains an arc (i, s, i) , *i.e.*, a loop on i . If $s = +$ (resp. $s = -$), this arc makes i tend to maintain (resp. negate) its state. It depends of course on whether i admits other in-neighbors than itself or not, and on the positive or negative influence of these eventual neighbors. In the case that i admits no other in-neighbors, it is trivial that i endlessly maintains its state if $s = +$, and negate it if $s = -$.

As mentioned above, an IG $G = (V, I)$ represents the existence of the interactions involved between the entities of V . Specifying the nature of these interactions, and the conditions under which they occur effectively, leads to relate G to a function f which define a BN. Then, G is the IG of f and is then denoted by $G(f) = (V, I(f))$. This is done by assigning a local transition function f_i to every $i \in V$ so that $\forall j \in V, \exists x \in \{0, 1\}^n, f_i(x) \neq f_i(\bar{x}^j) \iff (j, s \in \{+, -\}, i) \in I(f)$, where given $x = (x_1, \dots, x_n)$, $\bar{x}^j = (x_1, \dots, x_{j-1}, \neg x_j, x_{j+1}, \dots, x_n)$. More precisely, by denoting the set of the variables of two configurations x and y having a different value by $\Delta(x, y) = \{i \in V \mid x_i \neq y_i\}$, $G(f) = (V, I(f))$ is such that:

- $(i, +, j) \in I_f$ if and only if there exist $x, y \in \{0, 1\}^n$ with $\Delta(x, y) = \{i\}$ and $x_i = 0$ such that $f_j(x) = 0$ and $f_j(y) = 1$;

- $(i, -, j) \in I_f$ if and only if there exist $x, y \in \{0, 1\}^n$ with $\Delta(x, y) = \{i\}$ and $x_i = 0$ such that $f_j(x) = 1$ and $f_j(y) = 0$.

This specification induces the minimality of $G(f)$ because each arc represents an effective interaction.

Example 6 Figure 5 pictures the IGs associated with the ATGs of the BDSs defined from f and g in Example 1. For these case of elementary circuits, a positive arc $\{i, +, j\}$ says that j takes the value of i and a *negative arc* $\{i, -, j\}$ says that j takes the value of $\neg i$. Consider the positive circuit associated with f by following the directions of its arcs:

- Starting from $x_1 = 1$, we get the infinite sequence: $(1, 3, -2, 1, 3, -2, \dots)$.
- Starting from $x_1 = 0$, we get the infinite sequence: $(-1, -3, 2, -1, -3, 2, \dots)$.

The first (resp. second) dynamical behavior highlights the stable configurations $1, 2, -3$ (resp. $-1, -2, 3$) of f .

Consider the negative circuit associated with g :

- Starting from $x_1 = 1$ we get the infinite sequence $(-1, -2, -3, 1, 2, 3, -1, -2, -3, 1, 2, 3, \dots)$.
- Starting from $x_1 = 0$, we get the infinite sequence $(1, 2, 3, -1, -2, -3, 1, 2, 3, -1, -2, -3, \dots)$.

In both cases, the observed dynamical behavior highlights the stable cycle of g .

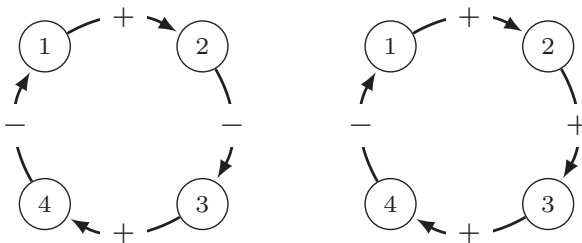


Fig. 6 (left) IG of f_2 (Example 4); (right) IG of g_2 (Example 5).

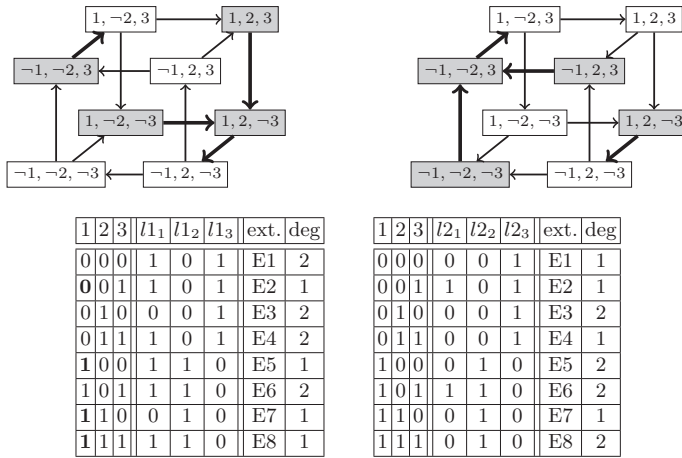


Fig. 7 (left) ATG and truth tables of function $l1$, and (right) of function $l2$, presented in Example 10 and Example 11. The gray rectangles are representing extensions of degree 1 (left) and stable configurations (right).

7 General fundamental results and applications in biology

By considering that BNs and their associated BDSs are good candidates for qualitatively modeling genetic networks (since established by the seminal papers [19, 43]), the presence of several attractors in their dynamical behaviors allows to model the cellular specialization. Indeed, if a genetic network controls a phenomenon of specialization, the cell will specialize (*i.e.*, will acquire a particular phenotype or a specific physiological function) according to the attractor toward which its underlying BDS evolves. A classical example of direct biological applications is the immunity control in bacteriophage λ , for which both lytic and lysogenic cycles of λ have been modeled in [42]. Another more tricky applications of BDSs in molecular systems biology concerns the floral morphogenesis of the plant *Arabidopsis thaliana* [26, 27]. Its dynamical behavior admits notably four stable configurations that correspond to the genetic expression patterns of the floral tissues, sepals, petal, stamens and carpels.

This model has also allowed to formally explain the role of the hormone gibberellin on the floral development [11]. These works and the numerous other ones using BDSs or more general discrete dynamical systems (DDSs) emphasized the essential role of studies aiming at understanding the formal relations between *interaction graphs* and *transition graphs* and their respective properties. They also clearly underlined the essential role of circuits, nowadays known as the behavioral complexity engines in dynamical systems. This comes in particular from Robert who established that, if the IG $G(f)$ of a DDS f is

acyclic, then f converges towards a unique stable configuration [34, 35]. Moreover, in [44], basing himself on asynchronous DDS, Thomas conjectured that $G(f)$ of an asynchronous DDS f must contain a positive (resp. negative) circuit, for the latter to admit several stable configurations (resp. a non-trivial attractor such as a stable cycle or a stable oscillation). These two conjectures were proved to be true [30–33].

Furthermore, in [30], the authors showed that an asynchronous positive (resp. negative) circuit of size n admits two attractors (resp. one attractor), namely two stable configurations x and its dual \bar{x} (resp. a stable cycle of length $2n$). Generalizations of this work to more complete combinations of circuits have been formally addressed in [25]. In [40], we obtained these results *via* the translation of BDSs into \mathcal{H} .

8 Representing BDS into \mathcal{H}

In [40], we studied the translation of positive and negative circuits into \mathcal{H} . This first step plays an essential role in cell regulation. But that approach left formulas of the type $(Hi \wedge Hj) \rightarrow Lk$ out of reach. Such formulas are essential to represent the binding of the regulatory region of a gene. In the sequel, the presented translation could be extended to any asynchronous BDS. This translation does not use nesting of modalities and therefore the SAT algorithms can be used.

8.1 Syntax representation of BDS

Let's recall that an asynchronous BDS is characterized by a function/ATG $f : X \rightarrow X$ such that $x = (x_1, \dots, x_n) \mapsto f(x) = (f_1(x), \dots, f_n(x))$, where each function $f_i : X \rightarrow \{0, 1\}$ is a local transition function. Also, remember that we consider that each x_i is an atom i , that the assignment x_i is a Boolean value i or $\neg i$, and therefore that each f_i is a Boolean formula.

Definition 3

- The translation of a local transition function f_i into \mathcal{H} is given by a set $TR(f_i)$ containing two formulas: $TR(f_i) = \{Hf_i(x) \rightarrow Li, Hf_i(\neg x) \rightarrow L\neg i\}$.
- The translation of $f : X \rightarrow X$ of a BDS in \mathcal{H} is the union of translations $TR(f_i)$ for all $i \in \{1, \dots, n\}$ such that $TR(f) = \bigcup_{i=1}^n TR(f_i(x))$.

From the correspondence given before (6.1), this translation is equivalently the translation obtained for $\mathcal{G}(f)$ and the truth tables of f .

Example 7 Consider $V = \{1, 2, 3\}$, $X = \{0, 1\}^3$ and the function f of Example 1, defined as $x = (x_1, x_2, x_3)$ and $f(x) = (f_1(x), f_2(x), f_3(x)) = (\neg x_2, \neg x_3, x_1)$ whose ATG of is pictured in Figure 1. The functions f_1 , f_2 and f_3 are translated into \mathcal{H} by; $TR(f_1) = \{H2 \rightarrow L\neg 1, H\neg 2 \rightarrow L1\}$, $TR(f_2) = \{H3 \rightarrow L\neg 2, H\neg 3 \rightarrow L2\}$, $TR(f_3) = \{H1 \rightarrow L3, H\neg 1 \rightarrow L\neg 3\}$.

Therefore we obtain the following global translation:

$TR(f) = \{H2 \rightarrow L\neg 1, H\neg 2 \rightarrow L1, H3 \rightarrow L\neg 2, H\neg 3 \rightarrow L2, H1 \rightarrow L3, H\neg 1 \rightarrow \neg L3\}$ that admits two stable extensions $E1 = Th(TR(f) \cup \{H1, H\neg 2, H3\})$ and $E2 = Th(TR(f) \cup \{H\neg 1, H2, H\neg 3\})$. This is shown by attempting to add to $F(G(f))$ each subset of $HY(G(f))$ and keeping only those among them that are the maximal ones consistent with $F(G(f))$. This can be done using a SAT solver.

When developing these extensions, we see that they are equivalent to their simplified forms:

- $E1 = \{H\neg 1, H2, H\neg 3, L1, L\neg 2, L3, \neg H1, \neg H\neg 2, \neg H3, \neg L\neg 1, \neg L2, \neg L3\}$
- $E2 = \{H1, H\neg 2, H3, L\neg 1, L2, L\neg 3, \neg H\neg 1, \neg H2, \neg H\neg 3, \neg L1, \neg L\neg 2, \neg L3\}$.

In order to ease the reading and abusing notations, from now on in the text and in the figures, the extensions will contain only the Li and $L\neg i$ that are true. So, here, $E1 = \{L1, L\neg 2, L3\}$ and $E2 = \{L\neg 1, L2, L\neg 3\}$. We can check that $E1$ and $E2$ are stable extensions (because for all i , $\neg Hi \in E1$ (resp. $E2$) $\implies L\neg i \in E1$ (resp. $E2$), and that $E2$ is the mirror of $E1$). These stables extensions correspond to the two fixed points of f .

Example 8 Consider function $g(x_1, x_2, x_3) = (\neg x_3, x_1, x_2)$ of Example 1. The translation in \mathcal{H} leads to the following set of formulas: $F(G(g)) = \{H1 \rightarrow L2, H2 \rightarrow L3, H3 \rightarrow L\neg 1, H\neg 1 \rightarrow L\neg 2, H\neg 2 \rightarrow L\neg 3, H\neg 3 \rightarrow L1\}$.

We obtain the following 6 equivalent ghost extensions: $E1 = \{L2, L3\}$, $E2 = \{L\neg 1, L3\}$, $E3 = \{L\neg 1, L\neg 2\}$, $E4 = \{L\neg 2, L\neg 3\}$, $E5 = \{L1, L\neg 3\}$, $E6 = \{L1, L2\}$.

• $E1, \dots, E6$ are extensions because they are consistent and it is impossible to add a hypothesis while remaining consistent. They are ghost extensions because in each of them there is a $\neg Hi$ (resp. $\neg H\neg i$) without $L\neg i$ (resp. Li).

- These extensions are of degree 1.

• In [40], we proved that there exists a permutation on the is that allows us to pass from $E1$ to $E2, \dots, E6$ to $E1$. This permutation of 6 ghost extensions represents the stable cycle of g .

Moreover, there are also two sub-extensions, $E7 = \{1, \neg 2, 3\}$ and $E8 = \{\neg 1, 2, \neg 3\}$ that contain neither Li nor $L\neg i$. Hence all the is are free and their degree is 3. These extensions correspond to the configuration of g , of indegree 0 of the underlying BDS. They represent the *Garden of Eden* of g .

Example 9 Consider function k , such that $k(x_1, x_2) = (x_2, x_1 \wedge \neg x_1 \wedge x_2)$, whose ATG is pictured in Figure 2 right. Function k_1 is translated into \mathcal{H} by the couple $TR(k_1) = \{H2 \rightarrow L\neg 1, H\neg 2 \rightarrow L1\}$ and function k_2 is translated by $TR(k_2) = \{H(1 \wedge \neg 1 \wedge 2) \rightarrow L2\}, H\neg(1 \wedge \neg 1 \wedge 2) \rightarrow L\neg 2\}$. Since $\neg(1 \wedge \neg 1 \wedge 2) = \neg 1 \vee 1 \vee \neg 2$, we finally obtain the following global translation into \mathcal{H} for k : $TR(k) = \{H2 \rightarrow L\neg 1, H\neg 2 \rightarrow L1, H(1 \wedge \neg 1 \wedge 2) \rightarrow L2\}, H(\neg 1 \vee 1 \vee \neg 2) \rightarrow L\neg 2\}$, which admits three extensions:

- A stable extension $E1 = Th(TR(k) \cup \{H\neg 1, H\neg 2\}) = \{L\neg 1, L\neg 2\}$;
- Two ghost extensions of degree 1: $E2 = Th(TR(k) \cup \{H1, H\neg 1\}) = \{L\neg 2\}$, and $E3 = Th(TR(k) \cup \{H2\}) = \{L1\}$.

³Function k may appear naive, because $x_1 \wedge \neg x_1 \wedge x_2 = \perp$ (\top is the logic formula *True* and \perp is *False*), which gives an equivalent translation $TR(h) = \{H2 \rightarrow L\neg 1, H\neg 2 \rightarrow L1, H\perp \rightarrow L2, H\top \rightarrow L\neg 2\}$. However, one of the aims of this study is also to show that we can deal with

The following examples are interesting because they get out of simple cycles.

Example 10 Consider function $l1(x_1, x_2, x_3) = (\neg x_2 \vee x_3, x_1, \neg x_1)$ whose ATG is represented by the Figure 7 (left) and IG by Figure 8 (left). The translation of l_2 is $TR(f_1) =$

$$\begin{aligned} &\{H(\neg 2 \vee 3) \rightarrow L1, H(2 \wedge \neg 3) \rightarrow L\neg 1, \\ &H1 \rightarrow L2, H\neg 1 \rightarrow L\neg 2, \\ &H1 \rightarrow L\neg 3, H\neg 1 \rightarrow L3\}. \end{aligned}$$

We obtain 4 ghost extensions of degree 1:

$$E1 = \{L\neg 2, L3\}, E2 = \{L1, L\neg 3\}, E4 = \{L2, L\neg 3\}, E7 = \{L1, L2\}.$$

and 4 sub-extensions of degree 2:

$$E3 = \{L\neg 2\}, E4 = \{L\neg 1\}, E5 = \{L3\}, E8 = \{L1\}$$

In Figure 7 (left), the extensions of degree 1, correspond to the gray configurations. We notice that there is no stable cycle.

Example 11 Consider function $l2(x_1, x_2, x_3) = (x_2 \wedge \neg x_3, x_1, \neg x_1)$. Its ATG is represented by the Figure 7 (right) and its IG by Figure 8 (right). The translation of l_2 is $TR(f_1) =$

$$\begin{aligned} &\{H(2 \wedge \neg 3) \rightarrow L1, H(\neg(2 \vee \neg 3)) \rightarrow L\neg 1, \\ &H1 \rightarrow L2, H\neg 1 \rightarrow L\neg 2, \\ &H1 \rightarrow L\neg 3, H\neg 1 \rightarrow L3\}. \end{aligned}$$

We obtain 2 stable extensions :

$$E2 = \{L\neg 1, L\neg 2, L3\}, E7 = \{L1, L2, L\neg 3\}$$

From these results, we retrieve the theorems about negative and positive double-cycles presented in [25] which gives a promising strong correspondence between \mathcal{H} and BDS. This correspondence will be formally studied in the rest of this article.

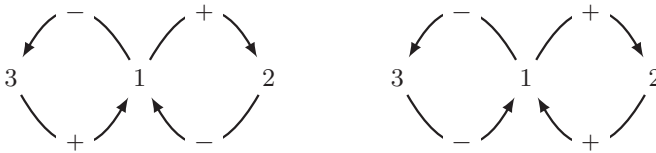


Fig. 8 (left) IG of $l1$, Example 10 and (right) IG of $l2$, Example 11

8.2 Semantic representation of ATGs into \mathcal{H}

This section gives a morphism between ATGs and Kripke models for the modal system T , which allows us to exhibit a morphism from hypothesis theories

functions of any kind, without the need of a pre-processing. The formalism of \mathcal{H} implicitly make the expected simplifications.

to ATGs. It uses *Kripke semantics* [21] presented in Section 3.2. In order to obtain these morphisms, we give an increased version of ATGs.

Definition 4 Let $V = \{1, \dots, n\}$ be a set of entities, $X = \{0, 1\}^n$ be a configuration space, $f : X \rightarrow X$ be a function with its associated ATG $\mathcal{G}(f) = (X, T(f))$. Remember that $T(f)$ is a set of edges corresponding to transitions. We now look at an increased version of $\mathcal{G}(f)$, namely $\mathcal{G}^*(f) = (X, T \cup \mathfrak{S})$ where \mathfrak{S} denotes the reflexivity such that (x, x) is a transition of $\mathcal{G}^*(f)$ for all $x \in \{0, 1\}^n$.

We can consider that $\mathcal{G}^*(f)$ is a Kripke structure whose universe is X and whose accessibility relation is $R = T(f) \cup \mathfrak{S}$. If we consider that any configuration $x \in X$ is a world, we get a Kripke model with R as its accessibility relation. As R is reflexive, it has the properties of system T . Therefore, we get an isomorphism between reflexive Kripke models and increased ATGs, from which it is trivial to obtain the related ATGs.

As the ATG $\mathcal{G}(f)$ is asynchronous, the accessibility relation R is such that, if $w_j \neq w_k$, then $w_j R w_k$ if and only if, w_k is reachable from w_j and differs from w_j by one and only one proposition. Under these conditions, the ATG of any BDS is a canonical Kripke structure. Given such a framework, for any world w_k and any entity x , $Lx = \top$ if and only if $x = \top$ for every w_k reachable from w_j .

In order to obtain a morphism between hypothesis theories and ATGs, we define the concept of a *projection* of an extension or of a sub-extension.

Definition 5 Consider a sub-extension, or an extension, E of \mathcal{H} . The *projection* of E on the system T is the set of formulas of E which does not contain the operator H .

Now, if $\mathcal{T} = \{HY, F\}$ is an hypothesis theory, and P is the set of the projections of the extensions or of the sub-extensions of \mathcal{T} , we obtain a morphism from \mathcal{T} to P , and therefore a morphism from hypothesis theories to Kripke models. Note that one does not get an isomorphism. Indeed the projections of two different extensions can be equal, and therefore be related to the same Kripke model.

Example 12 Figure 9 depicts the projection of function f given in Example 1, and its associated Kripke model $K(f)$. We remark that in order to get $K(f)$ from f , it is enough to inject the modality L at the right places into the cube, according to the corresponding Kripke frame. The eight nodes of $K(f)$ are the worlds, and the arcs express the accessibility relation. The two nodes in gray $\{L1, L-2, L3\}$ and $\{L-1, L2, L-3\}$ represent the two stable extensions from the translation of f . Their degree of freedom is 0. The other six nodes are sub-extensions since they are non-maximal. Their degree is 2. These six nodes form the unstable cycle of f , represented by bold transitions.

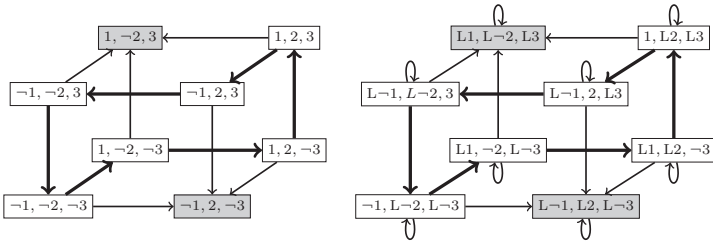


Fig. 9 (left) ATG of function f given in Example 1, and (right) its associated Kripke model.

Example 13 Figure 10 depicts the ATG of function g from Example 1 and the associated Kripke model. The six nodes in gray represent the ghost extensions of the translation of g . Their degree of freedom is 1 and correspond to the six configurations of the stable cycle of function g , represented by **bold arcs**. The other two nodes $\{1, \neg 2, 3\}$ and $\{\neg 1, 2, \neg 3\}$ are sub-extensions because they are non-maximal; their degree of freedom is 3.

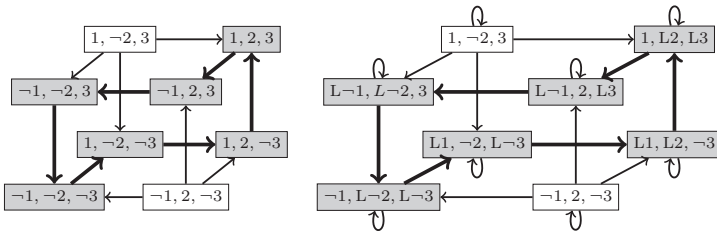


Fig. 10 (left) ATG model of function g given in Example 1 and (right) its associated Kripke model.

Example 14 Figure 11 depicts both the Kripke model and the ATG of function h given in Example 2.

Three nodes represent the three extensions of the translation of k : node $\{L\neg 1, L\neg 2\}$ represents the stable one, $\{1, L\neg 2\}$ and $\{L1, 2\}$ the two ghost ones of degree 1. There is also one sub-extension of degree 2, $\{1, 2\}$.

These examples suggest the following results.

9 Results

The existence of a morphism from hypothesis theories to ATGs, allows to prove the following theoretical results. Therefore, there is a strong link between configurations of a BDS and extension sets of the \mathcal{H} representation of this BDS.

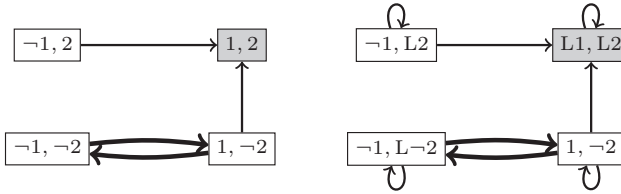


Fig. 11 (left) The ATG of h , (right) the corresponding Kripke model.

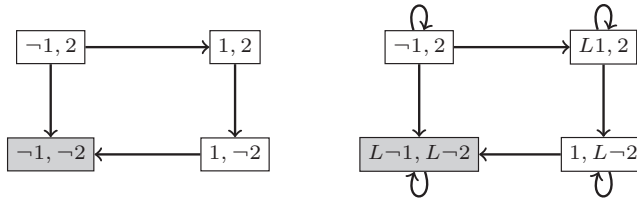


Fig. 12 (left) The ATG of k , (right) the corresponding Kripke model.

The generalization of the notion of degree of freedom of extensions allows us to configure ATGs. The *degree of a configuration* x , is the number of arcs coming out of x . By previous construction of the Kripke models associated with ATGs, it is obvious that, if w is the world associated with x , then x and w have the same degree.

Proposition 2 Let \mathcal{T} be an hypothesis theory, E be an extension or a sub-extension of \mathcal{T} , w be its projection and k be the degree of freedom of E . In the Kripke model associated to \mathcal{T} , there are exactly k distinct worlds, different from w , reachable from w .

Proof Since the degree of E is k , there are $\{i_1, \dots, i_k\}$ atoms free in E . For every $i \in \{i_1, \dots, i_k\}$, we have both $\neg Li \in E$ and $\neg L\neg i \in E$. Two cases are possible, either $i \in E$ or $\neg i \in E$. If $i \in E$, since $\neg Li \in E$, there exists a world w' accessible from w , and distinct from w , that contains $\neg i$. Regarding the second case, if $\neg i \in E$, since $\neg L\neg i \in E$, there exists a world w'' accessible from w , and distinct from w , that contains i . Therefore, for each $i \in \{i_1, \dots, i_k\}$, there is a world accessible from w , and distinct from w , that contains the opposite of i . Because w is related to an ATG all these accessible worlds are distinct. Hence there are k distinct worlds reachable from w . ■

Theorem 3 Let $\mathcal{G}(f)$ be an ATG of function f , and $TR(f)$ be its associated hypothesis theory. The following holds:

[1.] If $x = \{x_1, \dots, x_n\}$ is a stable configuration of $\mathcal{G}(f)$, then there exists an extension E of degree 0, issued from $TR(f)$, that contains $\{Lx_1, \dots, Lx_n\}$.

[2.] Let E be an extension of degree 0, issued from $TR(f)$, and w the projection of E . If x is the configuration related to w , then x is stable.

Proof Each statement is proved separately:

[1.] If x is a stable configuration of $\mathcal{G}(f)$, no edges can leave from x . By construction of the Kripke model, the same holds for the Kripke world w related to x . Hence the only word accessible from w is w , that is, for any $i \in w$ (resp. $\neg i \in w$), $Li \in w$ (resp. $L\neg i \in w$). Therefore, every i is fixed and the degree of the extension E , issued from $TR(f)$, is 0.

[2.] Let the projection of E be represented by the world w . Since E is of degree 0, from Proposition 2, the only reachable world from w is w . By construction of the Kripke model, the same holds for x . Therefore x is a stable configuration of $\mathcal{G}(f)$. ■

Theorem 4 *Let $\mathcal{G}(f)$ be the ATG of function f and $TR(f)$ be its associated hypothesis theory. Every stable cycle C of $\mathcal{G}(f)$ corresponds to a cycle of extensions of degree 1 in $TR(f)$.*

Proof The proof is similar to that of Theorem 3. Let $C = \{x_1, \dots, x_k\}$ be a stable cycle of $\mathcal{G}(f)$, and $W = \{w_1, \dots, w_\ell\}$ the set of extensions associated with C . By construction of the Kripke model, W is also a cycle of same length as C . Since C is stable, each of its configurations x_i admits only one outward arc. And the same property holds for w_i , i.e., the degree of w_i is 1. Therefore, all extensions of W are of degree 1. ■

Analog theorems were proved in the context of interaction graphs [40]. They correspond to the results given in [30]. With the same arguments as those used for the proofs of the previous theorems, we can show that if a BDS contains an unstable cycle C , it is represented by a set of extensions such that at least one of those is of degree greater than 1. Indeed, if the cycle is unstable, it contains a configuration x of degree greater than 1 and, by construction, the Kripke model associated with the BDS contains the extension E corresponding to x .

10 Conclusion

From Bioinformatics view point, this conversion of BDSs in Hypothesis Logic solves the problem of preference or priority in Biological Knowledge Representation. In [40], we studied in detail a translation of both positive and negative asynchronous circuits into (\mathcal{H}) . In this paper, we extend this translation to any asynchronous BDS, by showing that hypothesis logic captures some of their essential behavioral capacities, such as stable configurations and stable cycles that are specific attractors and unstable cycles. Of course, these results pave the way to further studies about how hypothesis logic could be used to represent all the dynamical richness of BDSs, by taking for instance into account their stable and unstable oscillations and other known properties related to the orbits.

Our study is only a first step toward a complete *logical* study of BDSs that, in the end, should allow us to clear both semantical and computational interesting properties of BDSs.

Data Availability

Research data are not shared.

Ethics declarations

Conflict of interest:

The authors declare no conflict of interest.

Ethical approval:

Not applicable.

Consent to participate:

Not applicable.

Consent for publication:

Not applicable.

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