Computing with Metabolic Machines

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Abstract

A protein can be thought of as a computational element, i.e. a processing unit able to transform an input into an output signal. Indeed, in a biochemical pathway, an enzyme reads the amount of reactants (substrates) and converts them into products. In this work, we consider the biochemical pathway in unicellular organisms (e.g. bacteria) as a living computer, and we program it in order to obtain desired outputs. The genome sequence is an executable code specified by a set of commands in a sort of ad-hoc low-level programming language. Each combination of genes is coded as a string of bits $y \in \{0, 1\}^L$. Each bit controls a gene set and therefore the chemical reaction associated with it. Through an optimal executable code stored in the "memory" of bacteria, we simultaneously maximise the concentration of two or more metabolites of interest.

Bacteria as von Neumann architectures



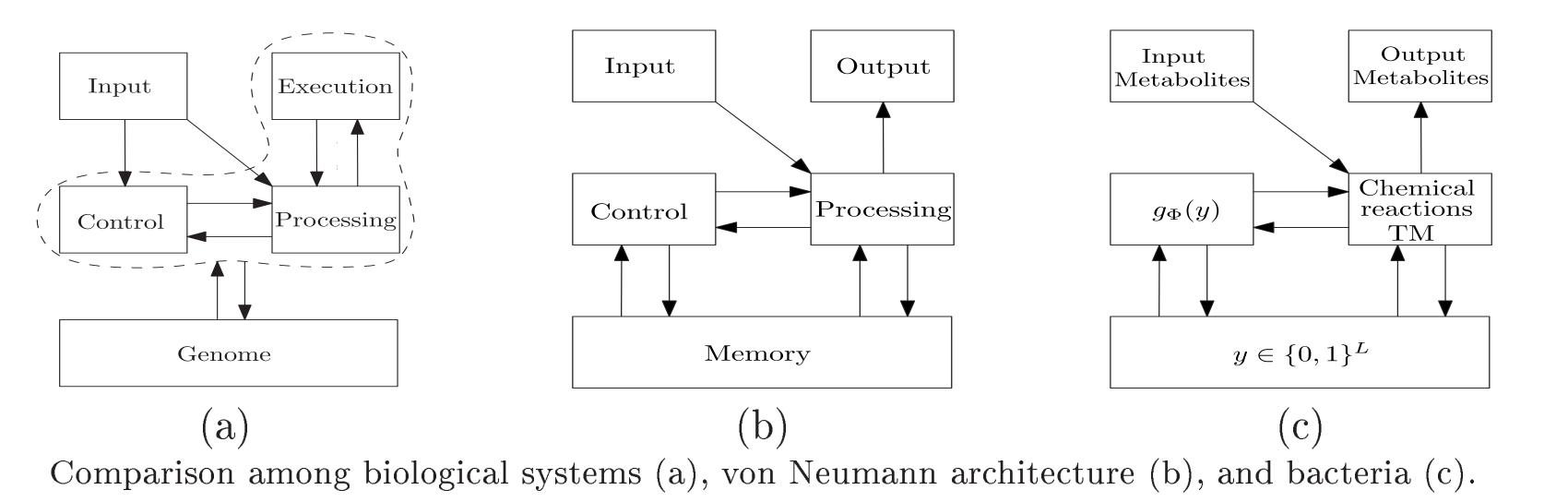
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Reaction networks as TM

We map the chemical reaction network to the **Minsky's Register Machine** (RM), i.e. a finite state machine augmented with a finite number of registers. The RM has been proven to be equivalent to the TM [2]. We define:

- The set of state species $\{D_i\}$, where each D_i is associated with the state *i* of the RM;
- The set of register species $\{H_r\}$, where each H_r is associated with the register rof the RM, and therefore represents the

Inspired by Brent and Bruck [1], who studied similarities and differences between biological systems and von Neumann computers, we propose a mapping between the von Neumann architecture and bacteria. This mapping suggests thinking of the metabolism as a Turing Machine (TM).



The bacterium takes as input the substrates required for its growth and, through its chemical reaction network, produces desired metabolites as output. The string y acts as a program stored in the RAM. Let Y be the multiset of the bits of y, and P(Y;p) be the set of all partitions of Y with p blocks. We formalise the control unit by defining the function

$$g_{\Phi}: \{0,1\}^L \longrightarrow \bigcup_{y \in \{0,1\}^L} P(Y;p)$$

molecular count of species r;

- The instruction inc(i, r, j) as the chemical reaction $D_i \to D_j + H_r$;
- The instruction dec(i, r, j, k) as either $D_i + H_r \rightarrow D_j$ or $D_i \rightarrow D_k$ depending on whether $H_r > 0$ or $H_r = 0$ respectively.

In our FBA approach, the variables are the fluxes of the reactions in the network, therefore a high flux corresponds to both a high rate of reaction and a high mass of products.

- In the increment reaction inc(i, r, j), H_r is positively correlated with the reaction flux;
- In the decrement reaction dec(i, r, j, k), when $H_r > 0$, it is negatively correlated with the reaction flux.

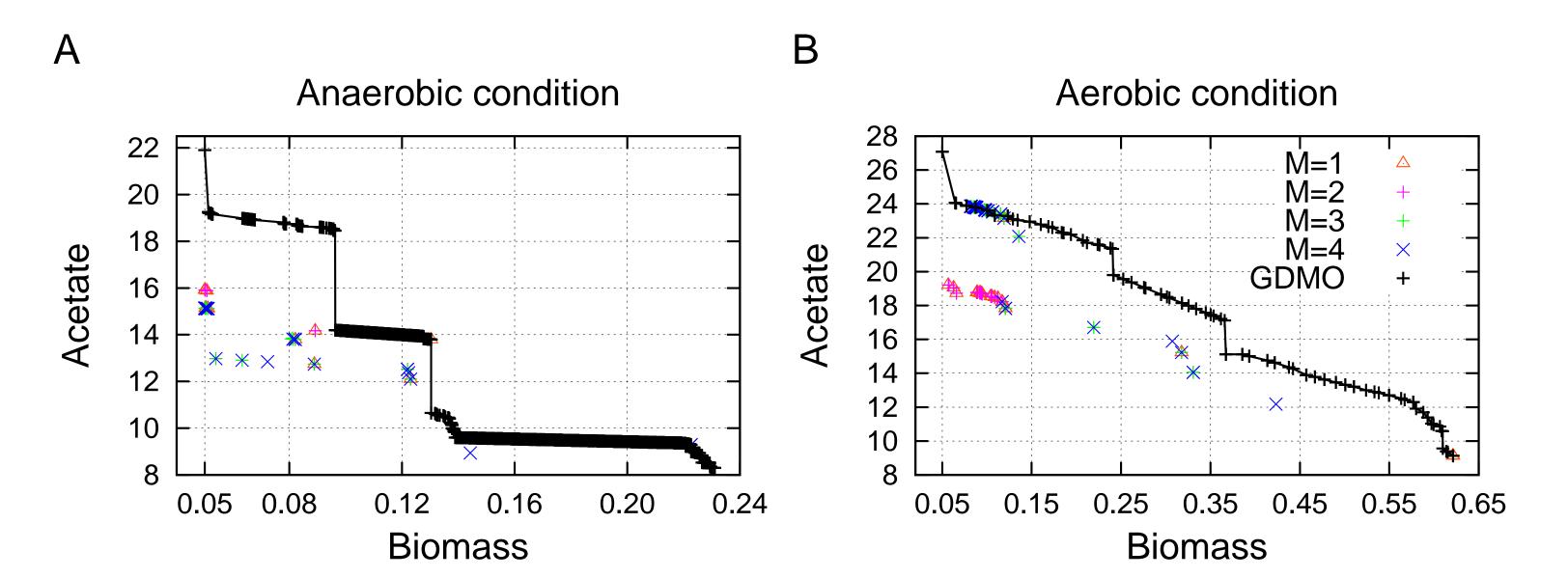
 $\bar{y} \in \{0,1\}^L \longmapsto \Pi \in P(\bar{Y};p).$

Each element of the partition Π is the submultiset b_s of all the gene sets that play a role in the reactions belonging to the s-th pathway. In other words, g_{Φ} turns syntax into semantics.

Genetic design of (living) computers

We program molecular machines using a novel algorithm called **Genetic Design through Multi-Objective optimisation (GDMO)**.

- Through a specific optimal code stored in the "memory" of the organism, we are able to simultaneously maximise the yield of two or more metabolites of interest.
- The genetic code, i.e. the "computation instructions" given to the machine, is represented by a Pareto-optimal string of bits $y \in \{0, 1\}^{L}$.



Conclusion

Since the simulated TM can be universal, the proposed mapping between metabolism and TM allows to perform any kind of computation, through a set of species and chemical reactions characterised by their flux. In principle, this means that bacteria can carry out at least any computation performed by a computer.

A program embedded in a bacterium, whose metabolism works like a TM, could be able to implement the knockout strategy found by GDMO. The minimisation of the number of knockouts ensures a low-effort, reliable and reproducible result, allowing cells to become programmable manufacturers of biochemical products of interest.

References

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Maximisation in anaerobic (A) and aerobic (B) conditions with glucose uptake rate 10 mmolh⁻¹ gDW⁻¹. The Pareto fronts of GDMO are in black. The results of GDLS depend on its parameters M and k [3].

	Wild Type	OptFlux	OptGene	GDLS	GDLS	OptKnock	OptKnock	GDMO	GDMO	GDMO
Acetate	8.30	15.129	15.138	15.914	_	-	12.565	13.797	19.150	-
		(82.3%)	(82.4%)	(91.7%)	-	-	(51.4%)	(66.20%)	(130.7%)	_
Succinate	0.077	10.007	9.874	_	9.727	9.069	-	-	_	10.610
		(12877%)	(12704%)	-	(12514%)	(12362%)	-	-	_	(13659%)
Biomass	0.23	n.a.	n.a.	0.0500	0.0500	0.1181	0.1165	0.1296	0.053	0.087
		n.a.	n.a.	(-78.4%)	(-78.4%)	(-77.9%)	(-49.6%)	(-43.91%)	(-77.10%)	(-62%)
k cost	n.a.	n.a.	n.a.	14	26	54	53	5	10	8

Best solutions (mmol h^{-1} gDW⁻¹) obtained by OptFlux ([4]), OptGene ([5]), GDLS ([3]), OptKnock ([6]) and GDMO on the *E. coli* K-12 MG1655 iAF1260 model ([7]), in anaerobic conditions with 10 mmol h^{-1} gDW⁻¹ of glucose uptake.

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