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"Integration of omics into metabolic flux distribution by complementary elementary mode analysis for large-scale metabolic networks"

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1. Background

2. Problems and objectives

3. Method

4. Results and discussion

5. Concluding remark

Introduction



Research Concept

Genome Omics Molecular Biology Medical data

Bioinformatics (Top-down): Parameter values are estimated to reproduce biological behaviors Systems Biology (Bottom-up): Mechanistic model construction based on molecular architecture





- We want to understand the system, we want to repair when some parts are failing; we want to improve the performance more.
- For example in human body, How genes and proteins that are working in the organism has been accumulated, such that to understand as a system of complex biological reaction is the systems biology.

Background



Metabolism is an important

biological processes



These are complex and highly interconnected

Metabolic disorder is related to a disease

It is important to understand properly of the metabolic networks using EM.

Figure 1: Metabolic pathway MAP

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Diabetes

- high blood pressure
- Cancer ...etc

Metabolic Pathways

□ Biochemical pathways are the organizational units of metabolism.

- Metabolism is the total of all chemical reactions carried out by an organism.
- □ A metabolic pathway has many steps that begin with a specific molecule and end with a product, each catalyzed by a specific enzyme.



Elementary mode analysis

Network-based metabolic pathway analysis:

- Elementary mode (EM) analysisExtreme pathways (ExP) analysis
- □EM is the minimal set of enzymes that can operate at steady state, while the set of extreme pathways is the systemically independent subset of the EMs.
- □ The EM coefficients (EMCs) indicate the quantitative contribution of their associated EMs and can be estimated by the maximizing the general objective function.

Problems

- Ordinary EM analysis is that the number of EMs suffers from a combinatorial explosion.
- EMs can be described by many scalar products of each EM, the predicted fluxes must be independent of them.
- Many organisms still do not provide any specific objective biological function.

Objectives

To overcome the existing problems, we proposed a several times faster and efficient EM algorithm named the complementary EMs (cEM) analysis.

◆EM decomposition [1] which generates the major EMs.

Alpha-spectrum [2] can be computed even when the flux is partially unknown.

✤MEP [3] to optimize the EMCs

General process



A flow chart of the cEM analysis



Alpha spectrum method [2]

Alpha spectrum method is applied to optimize the flux distribution. It is defined by:

Max/Min
$$\mathbf{v}_{i} = (v_{1}, v_{2}, ..., v_{n})^{t}$$

where, $i = 1, 2, 3, ..., n$;
$$\begin{cases} -1000 < v_{i}^{rev} < 1000 \\ 1e - 8 < v_{i}^{irrev} < 1000 \end{cases}$$
Subject to: $\mathbf{S} \cdot \mathbf{v} = 0$

Input: Stoichiometric matrix, ub, lb Output: V_{max} , V_{min}

EM decomposition method [1]

➢EM decomposition method is applied to generate the major EMs responsible for flux distribution.

Mixed integer linear programming (MILP)

≻It is an iterative method.

Input: Flux distribution, S, #reaction, #metabolites Output: EMs

Different objective functions

Methods	Objective Function	Advantage/Disadvantage	
LP	$\max v_{biomass} = \sum_{i=1}^{ne} p_{biomassi} \cdot \lambda_i$	Max biomass or ATP production are can vary between different organisms and physiological conditions. Thus the objective function are not good choice.	
QP	$\min\sum_{i=1}^{ne}\lambda_i^2$	Suitable when objective function cannot be defined in biological terms. Restricted for small or medium scale and depends on scalar product of EM.	
ECFLP	$Max / Min \lambda_i \ (i = 1, 2,, ne)$	ECFLP is not theoretical but empirical.	
MEP	$\max -\sum_{i=1}^{ne} \rho_{i} \ln \rho_{i}$ s.t. $\sum_{i=1}^{ne} \rho_{i} = 1; \sum_{i=1}^{ne} \rho_{i} x_{d,i} = v_{d}$	Straight forward formula and theoretically sound background. No need additional biological hypothesis or objective function and not depends on scalar product of EM	

Elementary mode analysis





Quantitative contributions $=\lambda_i \cdot P(\text{numuptake, i})$; where, i=number of EM and numuptake =the row in EM matrix P for uptake / input flux. The 4 cEM and flux distributions by cEM analysis are as follows:

$cEM = \begin{pmatrix} EM1 & EM2 & EM3 & EM4 \\ 0.5774 & 0.5774 & 0.5 & 0.5 \\ 0.5774 & 0 & 0 & 0.5 \\ 0 & 0.5774 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0 \\ 0.5774 & 0 & 0.5 & 0 \\ 0.5774 & 0 & 0.5 & 0 \\ 0 & 0.5774 & 0 & 0.5 \\ 0 & 0 & 0 & 0.5 \\ \end{pmatrix}_{7\times4} \qquad \begin{array}{c} Flux \ distributions \\ 100 \\ 50 \\ 25 \\ 50 \\ 50 \\ 50 \\ 50 \\ 50 \\ $						```	
$cEM = \left[\begin{array}{c} 0.5774 & 0.5774 & 0.5 & 0.5 \\ 0.5774 & 0 & 0 & 0.5 \\ 0 & 0.5774 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0 \\ 0.5774 & 0 & 0.5 & 0 \\ 0 & 0.5774 & 0 & 0.5 \\ 0 & 0.5774 & 0 & 0.5 \\ 0 & 0 & 0 & 0.5 \end{array} \right]_{7\times4} \qquad \qquad \begin{array}{c} 100 \\ 50 \\ 50 \\ 50 \\ 50 \\ 50 \\ 50 \\ 50 $		(EM1	EM 2	EM3	EM4		Flux distributions
$cEM = \begin{bmatrix} 0.5774 & 0 & 0 & 0.5 \\ 0 & 0.5774 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0 \\ 0.5774 & 0 & 0.5 & 0 \\ 0 & 0.5774 & 0 & 0.5 \\ 0 & 0 & 0 & 0.5 \\ \end{bmatrix}_{7\times4} \begin{bmatrix} 50 \\ 50 \\ 50 \\ 50 \\ 50 \\ 50 \\ 50 \\ 25 \end{bmatrix}$		0.5774	0.5774	0.5	0.5		100
$cEM = \begin{bmatrix} 0 & 0.5774 & 0.5 & 0 & & & & \\ 0 & 0 & 0.5 & 0 & & & & \\ 0.5774 & 0 & 0.5 & 0 & & & & & \\ 0 & 0.5774 & 0 & 0.5 & & & & & & \\ 0 & 0 & 0 & 0.5 & & & & & & \\ 0 & 0 & 0 & 0.5 & & & & & & & \\ 0 & 0 & 0 & 0.5 & & & & & & & \\ 0 & 0 & 0 & 0.5 & & & & & & & \\ 0 & 0 & 0 & 0.5 & & & & & & & & \\ \end{array} \right)_{7\times4} $		0.5774	0	0	0.5		50
$cEM = \begin{bmatrix} 0 & 0 & 0.5 & 0 \\ 0.5774 & 0 & 0.5 & 0 \\ 0 & 0.5774 & 0 & 0.5 \\ 0 & 0 & 0 & 0.5 \end{bmatrix}_{7\times4} \begin{bmatrix} 3.0 \\ 25 \\ 50 \\ 50 \\ 25 \end{bmatrix}$		0	0.5774	0.5	0		50
$ \left(\begin{array}{cccccccccccccccccccccccccccccccccccc$	cEM =	0	0	0.5	0		30
$ \left(\begin{array}{cccccccccccccccccccccccccccccccccccc$		0 5774	0	0.5	0		25
$ \left(\begin{array}{cccccccccc} 0 & 0.5774 & 0 & 0.5 \\ 0 & 0 & 0 & 0.5 \end{array}\right)_{7\times4} \qquad 50 \\ 25 \qquad 25 $		0.5774	0	0.5	0		50
$\begin{pmatrix} 0 & 0 & 0 & 0.5 \end{pmatrix}_{7\times 4}$ 25		0	0.5774	0	0.5		50
		0	0	0	0.5	$\int_{7\times4}$	25

Application in large-scale metabolic model

Model-I

The model-I was involved 140 metabolites and 156 reactions for the *E. coli pta-pfkA* gene knockout mutant undergoing adaptive evolution of 30 and 60 days under anaerobic condition.

Model-II

The model-II was involved 140 metabolites and 157 reactions for the *E. coli pta-adhE-pfkA-glk* gene knockout mutant undergoing adaptive evolution of 30 and 60 days under anaerobic condition.

Metabolic network map for E. coli



Quantitative contributions for input flux

Model	Methods	EM matrix (P)	$EMC(\lambda)$
	Ordinary EM	156 × 122126	122126 × 1
Model-I	cEM	156 × 202	202×1
	Ordinary EM	157 × 321416	321416×1
Model-II	cEM	157 × 295	295 × 1

Quantitative contributions = $\lambda_i \cdot P(\text{numuptake}, i)$ (*)

where, i=number of EM and numuptake =the row in EM matrix P for uptake / input flux.

Necessary and sufficient cEM



The employed cEMs and EMs and their quantitative contributions to input flux



Compare Results (Cont.)

Model-I

Model-II



Genetic Modification of Flux (GMF) [4]

GMF is an EM-based algorithm that couples with modified control effective flux (mCEF) and enzyme control flux (ECF).

mCEF was proposed based on CEF to estimate the gene expression patterns in genetically modified mutants in terms of specific biological function.

□ECF predicts how change in enzyme profile affects the flux distribution.

Compare Results (Cont.)

Model-I

Model-II



Pearson's correlation coefficient (r) and coefficients of determination (R^2) between the experimental flux and predicted flux.

Model	Condition	Method	Pearson's	Coefficients of
			Correlation (r)	determination (R ²)
		Ordinary EM	0.9980	0.9960
	Wild type	cEM	0.9982	0.9964
Model-I		Ordinary EM	0.9973	0.9947
Mutant type		cEM	0.9975	0.9950
		Ordinary EM	0.9639	0.9291
	Wild type	cEM	0.9634	0.9281
Model-II		Ordinary EM	0.9989	0.9978
	Mutant type	cEM	0.9989	0.9978

r range between 0.9634 and 0.9989 R^2 ranging from 0.9281 to 0.9978. These statistical analyses demonstrate the r and R^2 remarkably high, and provide statistically significant correlation between the experimental flux and predicted flux by cEM and ordinary EM analyses. Pearson's correlation coefficient (r) and coefficients of determination (R^2) between the experimental flux and GMF-predicted flux.

Model	Adaptive	Method	Pearson's	Coefficients of
	evolution		Correlation (r)	determination (R ²)
	30 days	Ordinary EM	0.9696	0.9401
		cEM	0.9680	0.9370
Model-I	60 days	Ordinary EM	0.9756	0.9519
		cEM	0.9743	0.9492
		Ordinary EM	0.8723	0.7610
	30 days	cEM	0.9873	0.9747
Model-II	60 days	Ordinary EM	0.9908	0.9817
		cEM	0.9841	0.9684

r range between 0.8723 and 0.9908 R² ranging from 0.7610 to 0.9817. These statistical analyses demonstrate the r and R² remarkably high, and provide statistically significant correlation between the experimental flux and GMF-predicted flux by proposed and ordinary method.

Calculation speed and accuracy

Model	Method		# EM	Total running time(s)	Prediction error
Model-I	Ordinary	CNA	122126	600+770.871=1370.871 ^a	0.0233
	EM	efmtool	122126	100+780.871=980.871ª	0.0233
	cEM		202	10+34+1.561=45.561 ^b	0.0268
Model-II	Ordinary CNA		321416	6000+1050.56=7050.56ª	0.0813
EM		efmtool	321416	200+1000.56=1200.56 ^a	0.0233
	cEM		295	12+38+1.805=51.805 ^b	0.0475

Predection error =
$$\sqrt{\frac{1}{m} \sum_{i=1}^{m} (v_{i,prediction} - v_{i,exp})^2}$$

^a The ordinary EM analysis consists of two steps (EM extraction and flux prediction by MEP) to predict the flux distributions. ^b The cEM analysis consists of three steps (α -spectrum, cEM extraction, and flux prediction by MEP).

Concluding Remarks

- We found 29 and 35 cEMs for model-I and model-II are enough to estimate the flux distributions, at which the prediction difference almost converges.
- The predicted (MEP & GMF) flux distribution by cEMs was very consistent with that by the ordinary EM analyses.
- The cEM method, where neither requires the initial generation of a full set of EMs nor any objective biological function, which is often computationally demanding, memory improvements and reduced the cost.

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