Computational Treatment of the Parameter Estimation Problem in Mathematical Immunology

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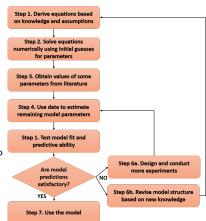
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Objectives of the work

- Develop and solve the inverse problem for the model of population dynamics of the HIV infection;
- Develop and estimate parameters for the model of labelled cells division;
- Compare the numerical optimization methods for the formulated problems solution.

Model developement and parameter estimation

- The mathematical description of the immune processes across different scales calls for the development of multi-scale models characterized by a high dimensionality of the state space and a large number of parameters
- For complex models, only a small subset of the model parameters can be derived or measured from the available experimental data. Most of the remaining parameters have to be estimated by solving the inverse problem.
- For high-dimensional models the parameter estimation problem is usually computationally demanding.



Parameter estimation problem

Mathematical model:

$$\begin{cases} \frac{\mathrm{d}y(t)}{\mathrm{d}t} &= F(y(t), \mathbf{p}), t \in [0, T] - \text{model equations;} \\ y(t) &= \left\{ y_i(t), i = 1, \dots, n, y_i(t) \in C^1(0, T) \right\} - \text{time dependent variables;} \\ y(0) &= y_0 - \text{initial conditions;} \\ \mathbf{p} &= \left\{ p_i \right\}, i = 1, \dots, m - \text{parameter vector.} \end{cases}$$
 (1)

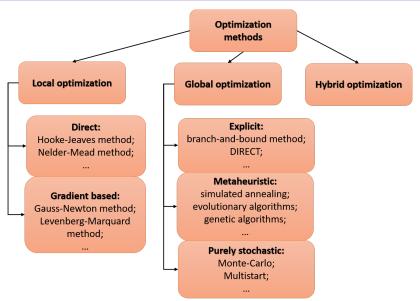
p = [a, b], where [a] is a vector of estimated components; {x_j, t_j}, j = 1, ..., K - experimental data. The parameter estimation problem can be formulated as:

$$\mathbf{p} * = \arg \min_{\mathbf{p} \in \Omega \subset \mathbb{R}^m} \Phi(\mathbf{y}, \mathbf{x}, \mathbf{p})$$
 (2)

A general statistical framework for parameter estimation is the Bayesian approach which under the assumption of a uniform prior distribution of the model parameters reduces to a maximum likelihood estimation (MLE). Assuming that the observational errors are normally distributed, time- and component-independent and the variance of observation errors is the same for all the state variables and observation times, the MLE reduces to the minimization problem for the least-squares function

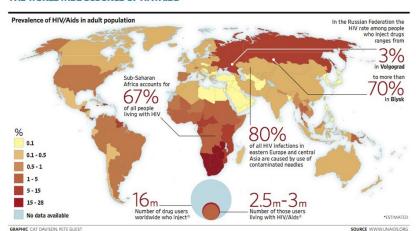
$$\Phi(\mathbf{p}) = \sum_{i=1}^{K} \sum_{i=1}^{n} (x_{i,j} - y_i(t_j))^2,$$
(3)

Numerical optimization methods

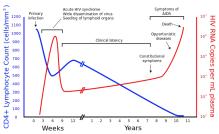


HIV epidemiology

THE WORLDWIDE SCOURGE OF HIV/AIDS



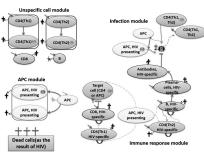
Mathematical model of HIV infection



https://en.wikipedia.org

- Most of the models only account for the acute phase and asymptomatic latency phase and cannot explain the progression to AIDS.
- There are different hypothesis for AIDS: population dynamics, virus evolution, et. al.

Mathematical model of HIV infection



Scheme notation
Infection
Death caused byCD8 lymphocytes (or antibodies for virus)
Secretion of virus particles
Killing (neutralization)
Homeostatic income
Death of infected cells
Proliferation
Antigen presenting
Transfer to another population
CD4 activity
Supression
Secretion of antibodies

- Marchuk-Petrov model of antiviral immune response was taken as a base;
- Model describes cellular and humoral immune reactions:
- The infection of target cells by HIV, i. e. the T helper lymphocytes (CD4 Th1 and CD4 Th2) and the antigen presenting cells (APC);
- The free virus- and the APC mediated modes of infection of CD4 T cells;
- The negative feedback of the infection and target cell destruction on the homeostasis of the lymphocytes is considered.
- Model contains 18 variables and 51 parameters, 32 parameters are estimated;
- Parameters were estimated for two datasets, characterizing different scenarios of infection dynamics;

Table: Model variables

Name	Variable	Initial value
D	number of antigen presenting cells (APC), cell/ml	5 · 10 ⁵
D_V	number of activated APC , cell/ml	0
H_F	number of CD4 Th1, cell/ml	4.5 · 10 ⁵
H_B	number of CD4 Th2, cell/ml	4.5 · 10 ⁵
В	number of B-lymphocytes, cell/ml	2.7 · 10 ⁵
P	number of plasma cells, cell/ml	10
F	number of antibodies, particle/ml	0
E	number of cytotoxic T-lymph., cell/ml	4.5 · 10 ⁵
D* H* H* V	number of inf. activated APC, cell/ml	0
H _F	number of inf. CD4 Th1, cell/ml	0
H_B^*	number of inf. CD4 Th2, cell/ml	0
\bar{V}	number of vir. particles, particle/ml	100
m	number of dead target cells(as infection result), cell/ml	0
H_{Esp}	number of HIV specific CD4 Th1, cell/ml	5
H_{Bsp}	number of HIV specific CD4 Th2, cell/ml	5
B_{sp}	number of HIV specific B-cells, cell/ml	3
E _{sn}	number of HIV specific cytotoxic T-cells, cell/ml	5
H* Esp	number of infected HIV specific CD4 Th1, cell/ml	0
H_{Bsp}^{*}	number of infected HIV specific CD4 Th2, cell/ml	0

Equations for uninfected unspecific cells and antibodies are written as follows:

$$\begin{split} \frac{\mathrm{d}D}{\mathrm{d}t} &= \alpha_D(\xi D^\mathbf{0} - D) - \sigma_D V D - \gamma_{DV} V D; \\ \frac{\mathrm{d}D_V}{\mathrm{d}t} &= \gamma_{DV} V D - \alpha_{DV} D_V - \sigma_D V D_V; \\ \frac{\mathrm{d}H_B}{\mathrm{d}t} &= \alpha_{H_B}(\xi H_B^\mathbf{0} - H_B) - \sigma_{H_B} H_B V - \sigma_{H_B}^D H_B D_V^*; \\ \frac{\mathrm{d}H_E}{\mathrm{d}t} &= \alpha_{H_E}(\xi H_E^\mathbf{0} - H_E) - \sigma_{H_E} H_E V - \sigma_{H_E}^D H_E D_V^*; \\ \frac{\mathrm{d}B}{\mathrm{d}t} &= \alpha_B(B^\mathbf{0} - B); \\ \frac{\mathrm{d}E}{\mathrm{d}t} &= \alpha_E(E^\mathbf{0} - E); \\ \frac{\mathrm{d}P}{\mathrm{d}t} &= b_P^0 \xi \rho_P(D_V + D_V^*)(H_{Bsp} + H_{Bsp}^*)B_{sp} + \alpha_P(P_\mathbf{0} - P); \\ \frac{\mathrm{d}F}{\mathrm{d}t} &= \rho_F P - \gamma_{VF} V F - \alpha_F F; \end{split}$$

Equations for infected unspecific cells are written as follows:

$$\begin{split} \frac{\mathrm{d}D_{V}^{*}}{\mathrm{d}t} &= \sigma_{D}V(D+D_{V}) - b_{D_{V}E}D_{V}^{*}E_{sp} - b_{D_{V}^{*}}D_{V}^{*}; \\ \frac{\mathrm{d}H_{B}^{*}}{\mathrm{d}t} &= \sigma_{H_{B}}H_{B}V + \sigma_{H_{B}}^{D}H_{B}D_{V}^{*} - b_{H_{B}E}H_{B}^{*}E_{sp} - b_{H_{B}^{*}}H_{B}^{*}; \\ \frac{\mathrm{d}H_{E}^{*}}{\mathrm{d}t} &= \sigma_{H_{E}}H_{E}V + \sigma_{H_{E}}^{D}H_{E}D_{V}^{*} - b_{H_{E}E}H_{E}^{*}E_{sp} - b_{H_{E}^{*}}H_{E}^{*}; \end{split}$$

Dynamics of viral particles and total number of dead cells are described by the following equations:

$$\begin{split} \frac{\mathrm{d}V}{\mathrm{d}t} &= \nu_{D_V} D_V^* + \nu_{H_E} (H_E^* + H_{Esp}^*) + \nu_{H_B} (H_B^* + H_{Bsp}^*) + N_{D_V} b_{D_V^*} D_V^* \\ &+ N_{H_E} b_{H_E^*} (H_E^* + H_{Esp}^*) + N_{H_B} b_{H_B^*} (H_B^* + H_{Bsp}^*) - \frac{kV(D_V + D_V^*)}{a(c + V)} \\ &- \gamma_{VH_B} V(H_B + H_{Bsp}) - \gamma_{VH_E} V(H_E + H_{Esp}) - \gamma_{VD} VD - \gamma_{VF} VF \\ &- \gamma_{VM} V; \\ \frac{\mathrm{d}m}{\mathrm{d}t} &= b_{D_V E} D_V^* E_{sp} + b_{D_V^*} D_V^* + b_{H_E^*} (H_E^* + H_{Esp}^*) + b_{H_E E} (H_E^* + H_{Esp}^*) E_{sp}; \end{split}$$

Equations for uninfected HIV-specific cells are written as follows:

$$\begin{split} \frac{\mathrm{d} H_{Bsp}}{\mathrm{d} t} &= \alpha_{H_B} (\xi \theta H_B^0 - H_{Bsp}) - \sigma_{H_B} H_{Bsp} V - \sigma_{H_B}^D H_{Bsp} D_V^* + \\ & 2 b_{H_B} (D_V + D_V^*) H_{Bsp} - b_{H_B}^P (D_V + D_V^*) H_{Bsp} B_{sp}; \\ \frac{\mathrm{d} H_{Esp}}{\mathrm{d} t} &= \alpha_{H_E} (\xi \theta H_E^0 - H_{Esp}) - \sigma_{H_E} H_{Esp} V - \sigma_{H_E}^D H_{Esp} D_V^* + \\ & 2 b_{H_E} (D_V + D_V^*) H_{Esp} - b_{H_E}^P (D_V + D_V^*) H_{Esp} E_{sp}; \\ \frac{\mathrm{d} B_{sp}}{\mathrm{d} t} &= \alpha_B (\theta B^0 - B_{sp}) + 2 b_B^P (D_V + D_V^*) (H_{Bsp} + H_{Bsp}^*) B_{sp}; \\ \frac{\mathrm{d} E_{sp}}{\mathrm{d} t} &= \alpha_E (\theta E^0 - E_{sp}) + 2 b_E^P (D_V + D_V^*) (H_{Esp} + H_{Esp}^*) E_{sp} - b_{ED_V} D_V^* E_{sp} \\ &- b_{EH_E} H_E^* E_{sp} - b_{EH_B} H_B^* E_{sp}; \end{split}$$

Equations for infected HIV-specific cells are written as follows:

$$\begin{split} \frac{\mathrm{d}H_{Bsp}^*}{\mathrm{d}t} &= \sigma_{H_B}H_{Bsp}V + \sigma_{H_B}^DH_{Bsp}D_V^* + 2b_{H_B}(D_V + D_V^*)H_{Bsp}^* - \\ & b_{H_B}^P(D_V + D_V^*)H_{Bsp}^*B_{sp} - b_{H_B}E_{sp}^*E_{sp} - b_{H_B^*}H_{Bsp}^*; \\ \frac{\mathrm{d}H_{Esp}^*}{\mathrm{d}t} &= \sigma_{H_E}H_{Esp}V + \sigma_{H_E}^DH_{Esp}D_V^* + 2b_{H_E}(D_V + D_V^*)H_{Esp}^* - \\ & b_{H_E}^P(D_V + D_V^*)H_{Esp}^*E_{sp} - b_{H_E}E_{sp}^*E_{sp} - b_{H_E^*}H_{Esp}^*; \end{split}$$

Negative feedback is described as follows:

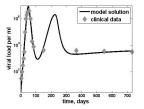
$$\xi = \frac{(1 - \epsilon m)}{\epsilon m + H_F^0 + H_B^0 + D^0};$$

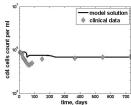
Minimized functional

$$\Phi(\mathbf{p}) = \sum_{j=1}^{17} [\log(CD4_{j,obs}) - \log(CD4(t_j))]^2 + \sum_{j=1}^{17} [\log(CD8_{j,obs}) - \log(CD8(t_j))]^2 + \sum_{j=1}^{17} [\log(V_j) - \log(V(T_j))]^2$$
(4)

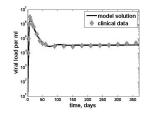
HIV model solution

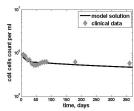
HIV dynamics model, data set 1:





HIV dynamics model, data set 2:



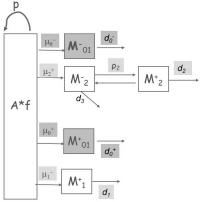




Mathematical model of labelled cells division

- Model describes the kinetics of proliferation of BrdU-labelled cells for SIV-infected primates;
- The main goal of the model is to check the hypothesis about chronic immune activation during the infection.
- The model version, describing also the dynamics of Ki67 was considered.

Mathematical model of labelled cells division



Zvi Grossman, Gennady Bocharov, 2006

- Experimental data is given for control and infected groups of animals; synthetic data is also considered;
- Parameters are evaluated for control and infected group simultaneously;

Mathematical model. Parameters

Table: Model parameters

Name	Biological meaning	Units	Range
μ_0^-	transition rate from A to M_{01}^{-}	ml/day	0.001 - 2
μ_0^+	transition rate from A to M_{01}^+	ml/day	0.001 - 2
μ_1^-	transition rate from A to M_1^+	ml/day	0.001 - 2
$\begin{array}{c} \mu_0 \\ \mu_0^+ \\ \mu_1^- \\ \mu_1^+ \\ \mu_2^- \\ d_0^+ \\ d_1 \end{array}$	transition rate from A to M_2^-	ml/day	0.001 - 2
d_0^{-}	death rate M_{01}^-	ml/day	
d_0^+	death rate M_{01}^{+}	ml/day	
d_1	death rate M_1^+	ml/day	
d_2	death rate M_2^+	ml/day	
d ₃	death rate M_2^-	ml/day	
ρ_2	transition rate from M_2^- to M_2^+	ml/day	0.001 - 1
ρ_3	transition rate from M_2^+ to M_2^-	ml/day	0.001 - 1
ρ	tuning parameter		0.3 - 3.0
ho f	tuning parameter		0.01 - 1
		ml/day	
р	basic proliferation rate for A	ml/day	0.1 - 2.0
A _{0 max}	maximal number for A	ml/day	1
LT	label injection interval delay	ml/day	1.5

Model equations

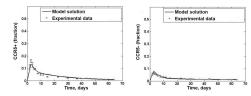
$$\begin{split} A^{L}(t) &= \begin{cases} A_{0\;max}(1-exp[-2pt]),\; 0 < t < LT;\\ A_{0\;max}(1-exp[-2p\,LT]),\; LT \leq t \leq LT + \Delta;\\ A_{0\;max}(1-exp[-2p\,LT])\; exp(-2p(t-LT-\Delta)),\; LT + \Delta < t. \end{cases} \\ \frac{\mathrm{d}M_{01}^{L-}}{\mathrm{d}t} &= \frac{\mu_{0}^{-}}{CCR5_{stac}^{-}} A^{L}f - d_{0}M_{01}^{L-};\\ \frac{\mathrm{d}M_{01}^{L+}}{\mathrm{d}t} &= \frac{\mu_{0}^{+}}{CCR5_{stac}^{+}} A^{L}f - d_{0}^{+}M_{01}^{L+};\\ \frac{\mathrm{d}M_{1}^{L+}}{\mathrm{d}t} &= \frac{\mu_{1}^{-}}{CCR5_{stac}^{+}} A^{L}f - d_{1}M_{1}^{L+};\\ \frac{\mathrm{d}M_{2}^{L-}}{\mathrm{d}t} &= \frac{\mu_{2}^{+}}{CCR5_{stac}^{-}} A^{L}f - \rho_{2}M_{2}^{L-} - d_{3}M_{2}^{L-} + \frac{CCR5_{stac}^{+}}{CCR5_{stac}^{-}} \rho_{3}M_{2}^{L+};\\ \frac{\mathrm{d}M_{2}^{L+}}{\mathrm{d}t} &= \rho_{2}\frac{CCR5_{stac}^{-}}{CCR5_{stac}^{+}} M_{2}^{L-} - \rho_{3}M_{2}^{L+} - d_{2}M_{2}^{L+}; \end{split}$$

Minimized functional

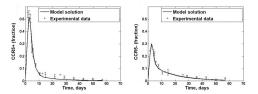
$$F = \Phi_{c}^{WLS}(\mathbf{p}) + \Phi_{i}^{WLS}(\mathbf{p}) + \frac{CCR5_{CONTROL}^{+}}{(CCR5^{+} + CCR5^{-})_{CONTROL}} - 0.075)^{2} + \gamma_{2}(\frac{CCR5_{INFECTED}^{+}}{(CCR5^{+} + CCR5^{-})_{INFECTED}} - 0.06)^{2} + \gamma_{3}(\frac{(CCR5^{+} + CCR5^{-})_{INFECTED}}{(CCR5^{+} + CCR5^{-})_{CONTROL}} - 0.16)^{2}$$
(5)

BRDU-labeled cell division model solution

Cell-division model, control group:



Cell-division model, infected group:



Progressive CD4+ central memory T cell decline results in CD4+ effector memory insufficiency and overt disease in chronic SIV infection. Okoye A1, Meier-Schellersheim M, et. al. Picker, Grossman (unpublished data)

Numerical methods used in numerical experiments

- TT TT global optimization method.
- CRS2 Controlled Random Search with local mutation. The idea of the algorithm is similar to the idea of genetic algorithms, which start with a random "population" of points, and randomly change these points according to some heuristic rules.
- rMLSL Multi-Level Single-Linkage with pseudo-random start points. MLSL is a subtype of multistart algorithm, which implements a sequence of local optimizations from random start points. The algorithm uses a clustering heuristic to avoid the re-introducing the previously founded local optima.
- qrMLSL Multi-Level Single-Linkage with quasi-random start points.
- rMLSL+SBPLX Multi-Level Single-Linkage with pseudo-random start points, Sublex method used for local optimizations.
- qrMLSL+SBPLX Multi-Level Single-Linkage with quasi-random start points, Sublex method used for local optimizations.
 - ISRES Improved Stochastic Ranking Evolution Strategy. The algorithm combines a mutation rule, realized with a log-normal step-size update and exponential smoothing, and differential variation, based on a Nelder-Mead-like update rule.
 - ESCH Evolutionary Algorithm. This is a modification of Evolutionary Algorithm, developed by Carlos Henrique da Silva Santos's.



TT global optimization method

- Method was introduced in INM RAS (Zheltkov, Tyrtyshnikov, et. al.)
- Method is based on the useful properties of the TT-decomposition and TT-cross interpolation method.
- Sequental and parallel versions of the method were implemented.

TT global optimization: algorithm

Algorithm 0.1: TT optimization $(A \in \mathbb{R}^{n_1 \times ... \times n_d}, r_{max}, max_it)$

```
\begin{aligned} & \text{for } k \leftarrow 1 \text{ to } d \\ & \text{do } P_k \leftarrow \textit{random} \\ & \text{for } it \leftarrow 1 \text{ to } \textit{max\_it} \\ & \begin{cases} [I_k, J_k] \leftarrow \textit{construct\_submatrix}(n_k, n_{k+1}, P_k) \\ [U, V, P_k] \leftarrow \textit{matrix\_cross}(A_k(I_k, J_k)) \\ P_k \leftarrow P_k \bigcup \textit{optimized}(P_k) \\ P \leftarrow P_1 \bigcup \ldots \bigcup P_d \\ P_k \leftarrow P_{k-1} \bigcup P_k \bigcup P_{k+1} \bigcup \textit{best}(P, r_{\textit{max}}) \\ \end{aligned} \end{aligned} & \text{return } (\textit{best}(P, 1))
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- Complexity: $O(dnr_{max}^2)$ functional evaluations, $O(dr_{max})$ local optimizations and $O(dnr_{max}^3)$ arithmetic operations.
- For parallel version parallel complexity: $O(r_{max})$ functional evaluations, O(1) local optimizations and $O(d + r_{max}^2)$ arithmetic operations

Numerical results

Locally optimized minimal values of the LSQ functional, obtained by global optimization methods. Results are given for HIV model $(M.\ 1)$ for two datasets (data 1 and data 2), and for labelled cell division model $(M.\ 2)$ for experimental data (data 1) and synthetic (data 2):

Method	M. 1, data 1	M. 1, data 2	M. 2 data 1	M. 2, data 2
TT	2.28	0.146	427	0.0055
CRS2	2.47	0.155	1164	49
rMLSL	2.50	0.186	759	2.4
qrMLSL	2.51	0.184	1062	67.2
rMLSL+SBPLX	2.13	0.144	428	0.04
qrMLSL+SBPLX	2.22	0.148	429	0.008
ISRES	2.34	0.156	526	1
ESCH	3.49	0.166	555	3.3

All methods were set to perform 10^6 functional evaluations for the first model and 10^8 for the second model.

Conclusions

- We formulated a mathematical model of HIV infection by extending the Marchuk-Petrov model of an antiviral immune response. The model considered a detailed description of the infection and immune response processes operative in HIV infection.
- We considered a model of BrdU-labelled cell division for healthy and SIV-infected primates.
- A number of existing optimization methods were explored to treat the parameter estimation problem for proposed models;
- The TT-based and MLSL hybrid optimization methods are in a lead group in all the experiments.

Thank you for your attention!

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