Bridging biological scales by linking agent-based models to intracellular and continuum biomechanics models

Shayn Peirce-Cottler, Ph.D.

Associate Professor of Biomedical Engineering

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The DEPARTMENT of BIOMEDICAL ENGINEERING School of Engineering and Applied Science • School of Medicine



Outline

- Introduction to ABM
- Multiscale Modeling
- ABM as a "bridge" in multiscale models
 - Linking ABM to intracellular models
 - Linking ABM to tissue-level biomechanics models
- Summary
- Future Work



Introduction to ABM

Emergent Phenomena



Agent-Based Modeling of Cells

. Discrete agents represent cells

. Agents interact with each other and with their environment



. Agent behaviors are governed by (*literature-based*) rules

Agent-Based Modeling of Cells

Netlogo Example

Agent Rules

- **11: cell behaviors**
- 85: adhesion molecule expression
- **69:** chemokine production & activation
- **30:** integrin activation

~200 total rules

~600+ papers



Agent-based Models



T.S. Deisboeck, 2000



Also in this issue: Molecular therapies for heart disease, Paracrine regulation of vascular apoptosis, Profilin in diabetic vascular disease, Degradation of apoptotic bodies, Melatonin and development

Official Publication of the Federation of American Societies for Experimental Biology April 2004, Volume 18, Number 6

Agent-based Models



A. Bailey et al. 2009

A.Qutub & A. Popel, 2009

Agent-based Models



S.H. Kim, J. Debnath, K. Mostov, S. Park, C.A. Hunt (2009)



S. Adra, T. Sun, S. MacNeil, M. Holcombe, R. Smallwood (2010)



M. Kim, S. Christley, J.C. Alverdy, D. Liu, G. An (2012)



B.N. Brown, I.M. Price, F.R. Toapanta, D. R. DeAlmeida, C.A. Wiley, T.M. Ross, T.D. Oury, Y. Vodovotz (2011)

Multiscale Modeling



Organ & Tissue Multi-Cell Intracellular Gene / Protein

Time

12

Organism

Spatial Scale (m)



J. Walpole, J.A. Papin, S.M. Peirce (in press)

Pathophisiology

At the organ level, **retinal detachment** can occur due to fibrosis of the basement membrane. Though taking only hours to days for complete detachment and **blindness**, this level of damage is end-stage; after years of fibrovascular remodeling, the retina is mechanically evulsed from the underlying tissue.

Measurement Techniques

This is a **macroscopic** event that is most easily observed using a standard opthalmascope.

Tissue level changes of the **microvasculature** reveal **micro-hemorrhages** as a result of vessel wall disruption. In proliferative disease, **neovascularization** is apparent in the periretinal vascular beds. These are the earliest clinical signs and are pathognomonic of the disease. Disregulation of vessel permeability can lead to **macular edema** and vessel dilatation.

Microscopic flame hemorrhages may be present on opthalmascopic exam. In addition, **cotton-wool spots** are often apparent due to local ischemic injury. Definitive measurements of permeability can be completed with **fundoscopic exam** and **fluorescein angiography**.

Vessel instability can be directly attributed to apoptotic cell death of pericytes and uncoordinated proliferation of endothelial cells. These changes occur throughout the course of the disease and are relevant both on short- and long-term time resolutions.

Pericyte apoptosis is triggered due to dephosphorylation of PDGF receptors, resulting in reduced survival signaling. This disruption is caused by PKC-delta activation and downstream phosphatase activity. These effects can be measured within days of exposure to hyperglycemia and are often persistent and irreversible. A simlar mechanism is responsible for endothelial proliferation. Pericyte drop out is typically measured microscopically using **immunihistochemical staining** of excised tissues. These observations can be made in murine models of diabetic retinopathy and are commonly studied as indicators of therapeutic efficacy.

Measurements of intracellular signalling are carried out using conventional **molecular biology techniques** such as immunoblotting, in situ hybridization, immunohistochemistry, and immunoprecipitation. **In vitro** assays and **in vivo** models provide tissue samples for analysis.





Multiscale Model Taxonomy



ABM Bridging to Intracellular

Capillary sprouting in the mouse embryoid body





F. Mac Gabhann, S.M. Peirce, V. Bautch (2012)

VEGF-NOTCH





ABM Initial Geometries









Embryoid Body



ABM



 $qVEGFR2 = qVEGFR2_{min} + (qVEGFR2_{max} - qVEGFR2_{min})e^{-k*Active_NOTCH}$ $\frac{dActive_NOTCH}{dt} = k_{Activation} * Inactive_NOTCH * \sum_{cells} DLL4 - k_{deg} * Active_NOTCH$

PDE



$$\frac{\partial [V]}{\partial t} = q_V + D_V \nabla^2 [V] - \sum_i \left(k_{on} [V] [M_i] - k_{off} [V \cdot M_i] \right) - \sum_i \left(k_{on} [V] [R_j] - k_{off} [V \cdot R_j] \right) - k_{deg} [V]$$

$$\frac{dR}{dt} = s_R - k_{int R} - \sum_i \left(k_{on} [V_i] [R] - k_{off} [V_i \cdot R] \right) - \sum_i \left(k_{dim} [V_i \cdot R] [R] - k_{off} [R \cdot V_i \cdot R] \right)$$

Governing Rules



Y. Hashemboy, F. Mac Gabhann, S.M. Peirce, V. Bautch⁰(2012)









Multiscale Model: Flk-1 Activation













t = 10

0















7.5

6.5

5.5





Multiscale Model Validation







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ABM Bridging to Tissue-Level



H. Hayenga, B.C. Thorne, P. Yen, J.A. Papin, S.M. Peirce, J.D. Humphrey (2012)



Multiscale Model





B.C. Thorne, H. Hayenga, J.D. Humphrey, S.M. Peirce (2011)

$$= \frac{2}{N} \sum_{j}^{N} \left(\frac{\left| C_{\text{NT}}^{\text{ABM}} - C_{\text{NT}}^{\text{CMM}} \right|}{C_{\text{NT}}^{\text{ABM}} + C_{\text{NT}}^{\text{CMM}}} + \frac{\left| M_{\text{NT}}^{\text{ABM}} - M_{\text{NT}}^{\text{CMM}} \right|}{M_{\text{NT}}^{\text{ABM}} + M_{\text{NT}}^{\text{CMM}}} \right)_{j} \\ + \frac{2}{S} \sum_{j}^{S} \left(\frac{\left| C_{\text{HT}}^{\text{ABM}} - C_{\text{HT}}^{\text{CMM}} \right|}{C_{\text{HT}}^{\text{ABM}} + C_{\text{HT}}^{\text{CMM}}} + \frac{\left| M_{\text{HT}}^{\text{ABM}} - M_{\text{HT}}^{\text{CMM}} \right|}{M_{\text{HT}}^{\text{ABM}} + M_{\text{HT}}^{\text{CMM}}} \right)_{j} \right)$$

TABLE 2. Listed are both the initial values of the parameters and the bounds that defined the search space used in the genetic algorithm to improve congruency between ABM and CMM predictions of smooth muscle and collagen mass via Eq. (5).

Parameter	Initial value	Lower bound	Upper bound	After genetic algorithm
K ^o	1	0.1	10	1.11
K	10	0.1	10	3.85
K.°	1	0.1	10	2.85
Km	10	0.1	10	8.75
MMP-1o	2.69E-04	2.69E-05	2.69E-03	9.47E-04
MMP-1%A	0.39	0.039	3.93	1.04
Co	0.009	0.0009	0.09	0.07
CTGF	114.94	11.49	1149.42	134.57
Mp	-1.45E+09	-1.45E+10	-9.69E+08	-1.53E+09
Mo	80,000	53333.33	120,000	6.12E+04
Mai	71020	7102	106530	9.89E+04
Ma2	100	66.66	1000	223.21
PDGF _{de}	4.79E-07	3.19E-07	7.19E-07	7.03E-07
PDGF ₀	4.17E-05	4.17E-06	6.25E-05	6.17E-05
$TGF \beta_{\sigma_0}$	1.65E-06	1.65E-07	1.65E+05	7.87E-06
$TGF\beta_0$	1.03E-04	1.03E-05	1.03E-03	3.69E-04

Note that 16 parameters were allowed to vary: CMM (top 4 rows) and ABM (bottom 12 rows). See Eqs. (1) and (2), Appendix, and Table 1 in Thorne *et al.*³⁷ for associated constitutive equations, definitions, or rules. Also listed are the final values of the parameters following minimization.

ABM Prediction

Normotensive













Model Validation

Experiment	Return to normal wall stress	Citation
Systolic pressure increase of 24% in rats	140 days	Wolinsky (1972)
Systolic pressure increase of 30% in rats	126 day	Matsumoto & Hayashi (1994)

Model	Return to normal wall stress
CMM Systolic pressure increase of 30% in mouse	70 days
ABM Systolic pressure increase of 30% in mouse	350 day
With congruency (both ABM and CMM)	125

Summary

Confidence Scoring of ABM Rules

1. ARTICLE AGREEMENT

0 = 0	
or 2 = 5	
3 or 4 = 7	
5 or 6 = 9	
7 and above = 10	

2. PHYSIOLOGICAL METHODS

In vivo, non-linear, residual, anisotropy, heterogeneity accounted for = 10 Ex vivo, pre-conditioned, acute testing, comp. sound = 8 Ex vivo, cultured, pre-conditioned, comp. sound = 6 In vitro, acute testing, environment sound = 4 In vitro, culture = 2

3. SIMILARITY

Cell type: endothelial or SMC = 10; all others = 0 Organ system: arterial = 10; other vessels or organs = 0 Species: mouse = 10; all others = 0 Environmental conditions: *in vivo* = 10; all others = 0^*

4. DATA TYPE

Numerical = 10 Theoretical = 6 Descriptive = 2 Measured directly = 10; protein determination by absorbance, electrophoresis Measured indirectly = 6; amount inferred through the magnitude of fluorescence/stain intensity Extrapolated = 4 Descriptive = 2

B.C. Thorne, H. Hayenga, J.D. Humphrey, S.M. Peirce (2011)

Confidence Scoring of ABM Rules

Rule	SMC production of PDGF-AB (stress dependent)				
	Researcher 1		Research	Researcher 2	
Relevant papers	Li et al. (1995)	Ma et al. (1999)	Li et al. (1995)	Ma et al. (1999)	
1. Article agreement	0	7	5	5	
2. Physiological methods	6	4	6	6	
3a. Same species	0	0	0	0	
3b. Same organ	10	10	10	10	
3c. Same cell type	10	10	10	10	
3d. Same <i>in vivo</i> state	5	5	10	10	
3. Similarity metric total:	6.25	6.25	7.5	7.5	
4a. Numerical	10	10	10	10	
4b. Measured directly	7	7	5	5	
4c. Many data points	2	4	2	2	
4. Data type total	6.33	7	5.67	5.67	
Average confidence	4.65	6.06	6.04	6.04	
Composite score	5.3	5.36		6.04	

B.C. Thorne, H. Hayenga, J.D. Humphrey, S.M. Peirce (2011)

REVIEW



Open Access

Relational grounding facilitates development of scientifically useful multiscale models

C Anthony Hunt^{1*}, Glen EP Ropella², Tai ning Lam³ and Andrew D Gewitz⁴



Utility of Computational Modeling

Identify key parameters

(Drug target identification)

- Quantitatively pinpoint voids in understanding
 - (Mechanism of action)
- Compare alternative hypotheses
 (Combination therapies)
- Suggest and refine new hypotheses

(Determine side effects & compensatory pathways)

Calculate what can't be measured

(Predict dosing and potency)

Accelerate discovery process



Utility of Multiscale Modeling



In our experience...

- Requires close collaboration & trust
- Conceptual challenges > computational challenges
- Experimental validation is no less important but it is easier?
- Model simplification strategies and choice of parameters in one model can impact predictions of the other
 - ✓ Sensitivity analysis is important
 - Internal validity checking
 - ✓ Validation against experimental data

Future Work

Multiscale FE and ABM that predicts muscle tissue adaptation to surgery



S. Blemker

Multiscale FE and ABM that predicts muscle tissue adaptation to surgery















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