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Institute for in silico Medicine

Use of machine learning and modelling to improve diagnosis and treatment of ischaemic stroke

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Outline

Cardiovascular applications

Musculoskeletal applications



Use of machine learning methods to develop a methodology for differentiating between **cerebral vasospasm (VS)** and **ischaemic stroke (IS)**

Cerebral vasospasm (VS)



http://www.idorsia.com

• Progressive narrowing of arteries after stroke/SAH

Major cause of cerebral ischaemia

Findlay et al., Can J Neurol Sci, 2016

Ischaemic stroke (IS)



http://www.enableme.org.au

 Blood supply to brain is cut off or severely reduced

• Leading cause of long term disability

Phipps, et al., BMJ, 2020

VS or IS?

Different treatment strategies:

Treatment of VS

- Pharmacological
- Endovascular (balloon and catheter **angioplasty**)

Similar diagnostic techniques:

- Imaging (CT, MRI, ...)
- Transcranial Doppler

Treatment of IS

- Thrombolytic drugs
- Mechanical removal (balloon and catheter thrombectomy)

Transcranial Doppler

- Measurement of Doppler frequency shift to estimate the blood velocity
- Portable and non-invasive
- Abnormal waveforms in arteries affected by VS and IS
- Low sensitivity to alterations in peripheral vessels

Pulse waves in the cardiovascular system



O. Alexandrov https://commons.wikimedia.org/w/index.php?curid=3148138

- Pressure waves originate from intermittent contractions of the heart
- Wave propagate through the network of elastic vessels
- Waves are reflected at discontinuities

Pulse waves in the cardiovascular system

 Incident and reflected waves superimpose to determine the observed waveform





T. Walsh http://www.ophysics.com

1D cardiovascular model (openBF)

- Incompressible flow in tapered elastic vessels
- Method of characteristics
- Finite volume method
- Open source

$$\begin{cases} \frac{\partial A}{\partial t} + \frac{\partial (Au)}{\partial x} = 0, \\\\ \frac{\partial (Au)}{\partial t} + \frac{\partial (Au^2)}{\partial x} + \frac{A}{\rho} \frac{\partial P}{\partial x} = -8\pi \frac{\mu}{\rho}u, \\\\ P = P_{ext} + \beta \left[\left(\frac{A}{A_0}\right)^{1/2} - 1 \right], \quad \beta = \sqrt{\frac{\pi}{A_0}} \frac{Eh_0}{1 - \sigma^2}, \end{cases}$$



Melis et al., Int J Numer Meth Biomed Eng, 2017

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Gaussian process statistical emulators



• GPE is trained with few runs of the original model

- GPE is used to perform sensitivity and uncertainty analysis, reducing computational time
- Identification of waveform features strongly correlated with the pathology in exam

Melis et al., Int J Numer Meth Biomed Eng, 2017

Sobol's sensitivity analysis: VS biomarker

Which inputs, or combination of inputs, have the greatest effect on output variables that can be observed in a clinical setting?



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$\min(\partial_t P)$	90	7	6	0	2	5	3	5	0	1
$\min(\partial_{tt}P)$	94	6	4	0	0	4	3	3	0	0
$\min(Q)$	71	22	36	7	6	66	24	23	5	2
$\min(\partial_t Q)$	88	5	12	0	4	10	1	6	0	1
$\min(\partial_{tt}Q)$	73	7	25	1	5	8	4	9	0	0
$\min(u)$	97	0	2	0	0	1	1	1	0	0
$\min(\partial_t u)$	89	1	6	0	6	4	2	5	0	1
$\min(\partial_{tt}u)$	93	1	5	0	1	1	2	3	0	0
mean(P)	3	0	1	98	0	0	0	0	3	0
$mean(\partial_t P)$	50	33	46	9	5	32	23	33	1	3
$mean(\partial_{tt}P)$	31	50	41	32	0	31	49	45	3	0
mean(Q)	81	9	17	14	4	60	36	52	14	2
$mean(\partial_t Q)$	59	54	54	0	1	46	43	43	1	0
$mean(\partial_{tt}Q)$	65	35	65	0	1	54	27	46	1	1
mean(u)	97	0	2	0	0	1	1	1	0	0
$mean(\partial_t u)$	92	4	13	2	0	8	2	11	0	0
$mean(\partial_{tt}u)$	88	16	35	0	2	29	10	28	0	2
$\max(P)$	18	1	2	81	0	1	1	1	З	0
$\max(\partial_t P)$	93	7	4	0	1	3	3	4	0	0
$\max(\partial_{tt}P)$	93	6	4	0	1	3	3	4	0	0
$\max(Q)$	92	3	16	4	1	41	5	24	4	1
$\max(\partial_t Q)$	86	2	17	3	2	28	1	15	2	1
$\max(\partial_{tt}Q)$	83	8	13	0	6	9	4	7	0	0
$\max(u)$	97	0	2	0	0	1	1	1	0	0
$\max(\partial_t u)$	97	1	2	0	0	1	1	1	0	0
$\max(\partial_u u)$	88	3	8	0	5	3	3	4	0	0

 $R_0 E \ell R_n C_n R_0 E \ell R_n C_n$

 \mathbf{T}_i \mathbf{H}_i

CV biomarker	\mathbf{T}_{R_0}	\mathbf{H}_{R_0}
mean(u)	97.43	0.82
$\max(u)$	97.28	0.84
$\min(u)$	97.23	0.93
$\max(\partial_t u)$	96.83	0.90
$\min(\partial_{tt}P)$	93.76	3.62
$\max(\partial_{tt}P)$	93.05	3.35
$\min(\partial_{tt}u)$	92.98	1.16
$\max(\partial_t P)$	92.52	3.48

Distal arteries: min(u_t)





Melis et al., J Biomech, 2019

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The plan: IS

- Simulate complete physiological cerebral network to have a baseline
- Simulate IS in a variety of common locations
- Identify pool of biomarkers through GP based SA

Ideas for collaboration?

- Waves reflect due to tortuosity, bending and other 3D geometric features: does the same analysis in 3D FSI CFD confirm the findings of 1D models?
- Explore the use of other statistical emulators



Musculoskeletal modelling in CompBioMed2

Ivan Benemerito, Nino La Mattina, Marco Viceconti, Enrico Dall'Ara, Pinaki Bhattacharya, Shannon Li, Alberto Marzo









The problem /1

- Bone drugs are long-term therapies that aim to reduce the risk of bone fracture associated with low-energy impacts (fragility fractures)
- The risk of hip fracture in the general population over-50 is only 2% over ten years
- To observe 100 hip fractures we would need to follow up for 10 years over 5000 patients

The problem /2

- Efficacy of recent bone drugs was demonstrated through indirect endpoints, such as changes in bone mass
- Bone mass can explain only 60-70% of hip fractures
- Serious possibility that the efficacy found in the phase III clinical trial, will not translate into effectiveness in future HTA studies

The problem /3

- Many of these new drugs can be used only once during the patient life, and only for limited time: it would be important to know when is the best time to use them
- Clinical trials aimed at optimising the treatment protocol with two or more drugs would be prohibitively expensive, so alternatives are required



To develop collaboratively an *in silico* trials platform to evaluate the efficacy of new bone drugs on human cohorts, from limited pharmacodynamics data on the new drug obtained on mice

An hypothetical model



1: A **validated** patient-specific model that predicts the risk of hip fracture today





2: A **validated** mouse-specific model that can provide an estimate of the drug effect

3: A **validated** stochastic population-specific bone remodelling algorithm model that predicts changes in bone over time

1 - CT2S: from imaging to models



Basu et al., Biomater Med Devices Artif Organs. 1985



1 - ARF0 fall simulator

- Multiscale model of fall, body-floor damping, femur deformation
- Full stochastic modelling of fall
- Stochastic modelling of uncertainties (i.e. soft tissue damping)
- Accuracy: 0.82 0.84



3 - Bone remodelling algorithm



Strain energy

Maximum



Red = experimental remodelling Yellow = predicted correctly by model



Cheong et al., BMMB, under revision

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Software architecture



Clinical studies

- 1. Sheffield cohort
 - a) 98 women, 50% with hip fracture
 - b) Perfect controlled validation cohort
 - c) Simulations run on USFD cluster
- 2. Virtual cohort
 - a) 1000 virtual patients generated by statistical atlasing of the Sheffield cohort
 - b) Simulations run on SurfSara HPC
- 3. Bologna cohort
 - a) Up to 500 cases, 5% with hip fracture
 - b) Validation cohort for virtual population
 - c) Simulations run on UNIBO cluster

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