eloppement d'instruments médicaux en physique méd

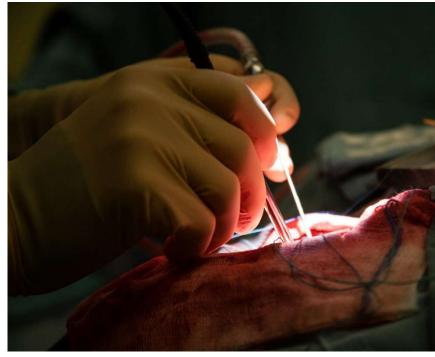
Frederic Leblond, PhD

Director, Laboratory for Radiological Optics ring Physics Department, Polytechnique Montreal ch Center, University of Montreal Medical Center









ABORATORY FOR RADIOLOGICAL OPTICS

ineering School versité de Montréal Campus

OLYTECHNIQUE Iontréal

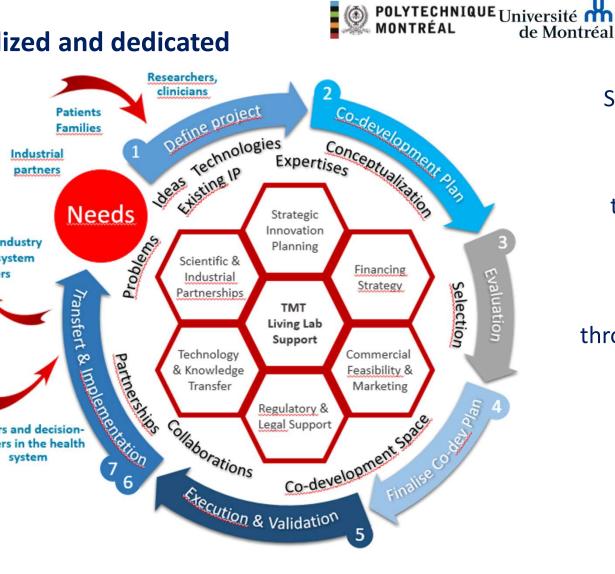


Montreal Neurological Institute and Hospital

P McGill

neun

FransMedTech Institute of Montreal A consortium funded b Canada First Research Excellence Fund (100M\$, 7 years)



Supports the **development** & **validation** of r generation medical technolog

CHU Sainte-Justine

Le centre hospitalier

Cardiovascular – Musculoskeletal - Car

Hôpital général juif

Jewish General Hospital CHUM

to facilitate their **implementation** in the heat system or industion

Train the next generation of profession through HQP and student grants and personali training progra

Living Lab mo

Transdisciplinary, intersectoral collabora research, open innovation and creati



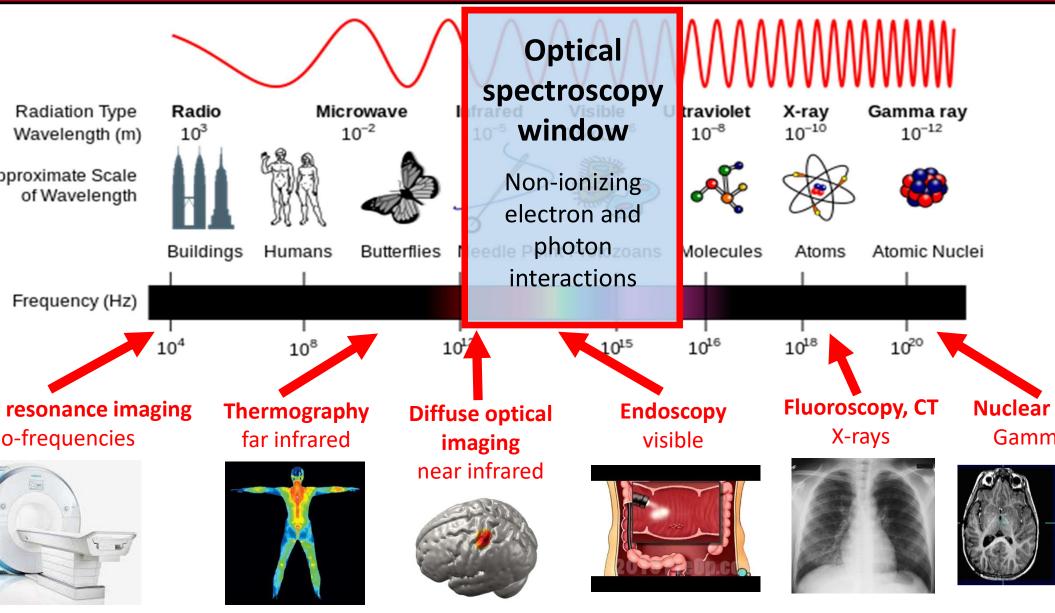
<u>- HOW CAN LIGHT-TISSUE INTERACTIONS BE EXPLOITED</u> OR MOLECULAR CHARACTERIZATION ?





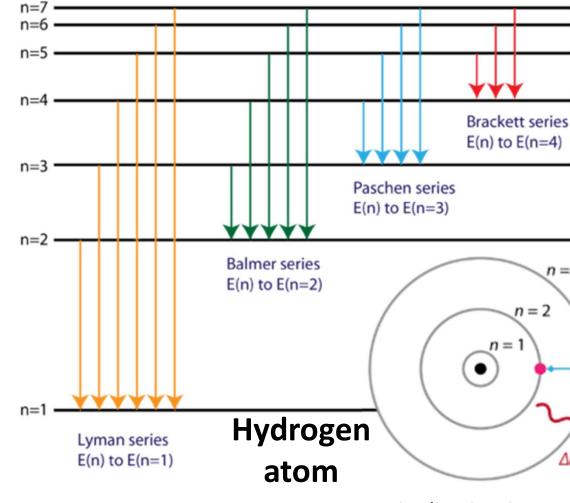


MEDICAL IMAGING ACROSS THE ELECTROMAGNETIC SPECTRUM



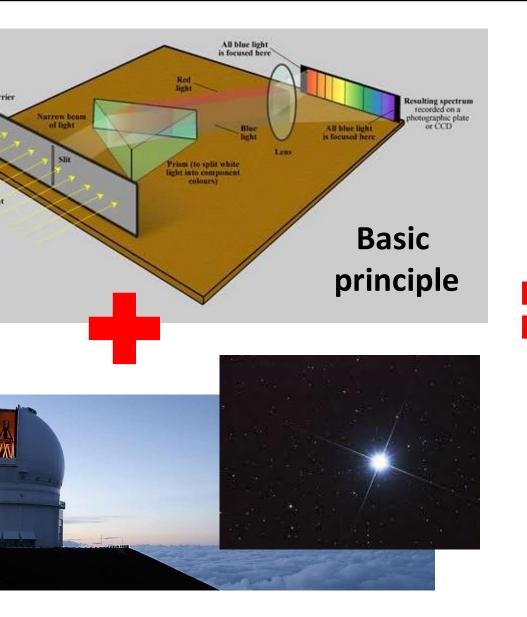
<u>/ERY</u> SHORT INTRODUCTION TO QUANTUM MECHANICS EXCITATION OF ATOMS AND MOLECULES

- nentary particles are wave ctions quantifying their **probability** e a given location in space
- tronic **energy levels** in atoms and ecules are discrete
- t is composed of discrete energy kets with a frequency and a elength : **photons**
- ntum mechanics : **selection rules** ating which **photons** can excite **trons** in atoms and molecules

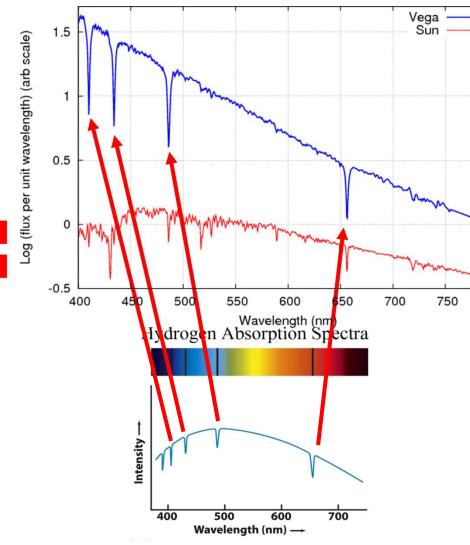


Credits: CK-12 Found

WHAT IS SPECTROSCOPY ?



Absorption spectrum of a sta (electronic states)



THE MAKE-UP OF LIFE

Atoms

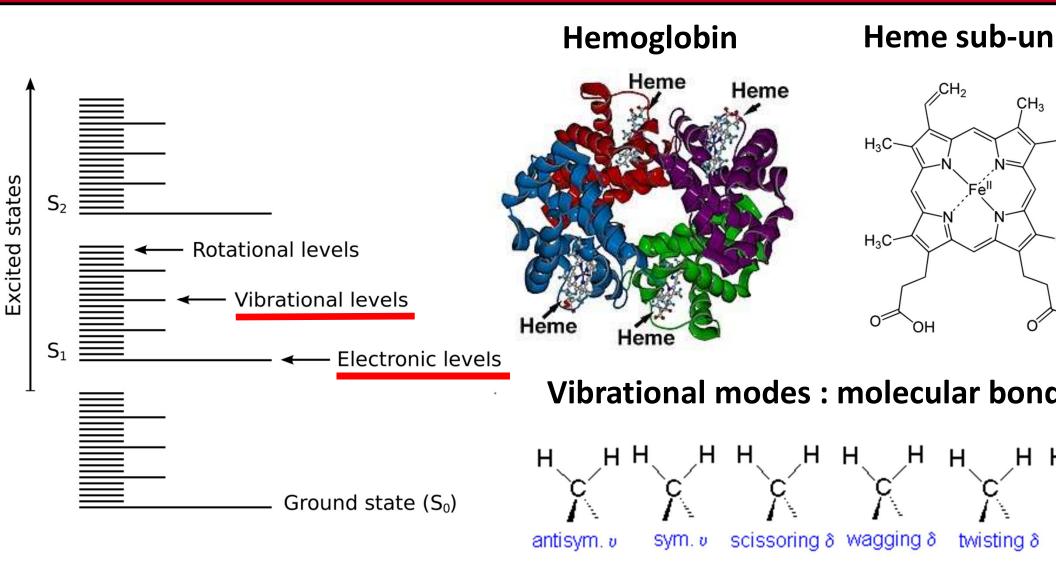
Complex biomolecules

IMATE PERCENTAGE OF CHEMICAL SUBSTANCES IN A CELL

Main class of chemical substances	Approximate percentage composition		
Water	80.0	Inorganic	
Inorganic salts	1.0	Inorganic	
Carbohydrates	1.0	1	
Lipids	0.5		
Proteins	12.0		
Nucleic acids	2.0	Organic	
Other organic substances	0.5		

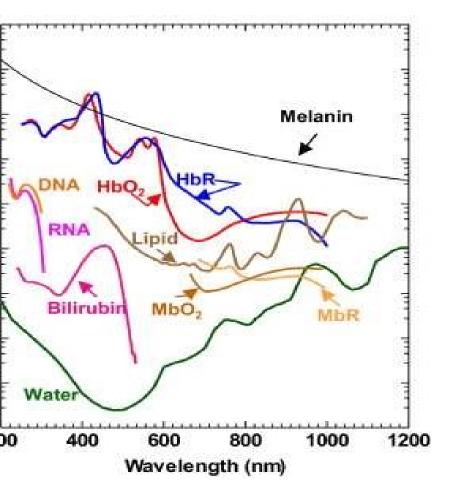
Elements	Approximate weight (percentage)			
 Oxygen Carbon Nitrogen Hydrogen Calcium Phosphorous Chlorine Sulphur Potassium Sodium Magnesium Iodine 	62.00 20.00 10.00 3.00 2.50 1.14 0.16 0.14 0.11 0.10 0.07 0.014	About 95% major elements About 4.25% minor elements	Essential > elements about 99.3	
13.Iron	0.010			
14.Copper, Cobalt, Zinc, Silicon, Manganese, Aluminium Molybdenum, Florine etc.	0.756	About 0.75% > trace elements	Trace > elements about 0.7	
	100	100	100	

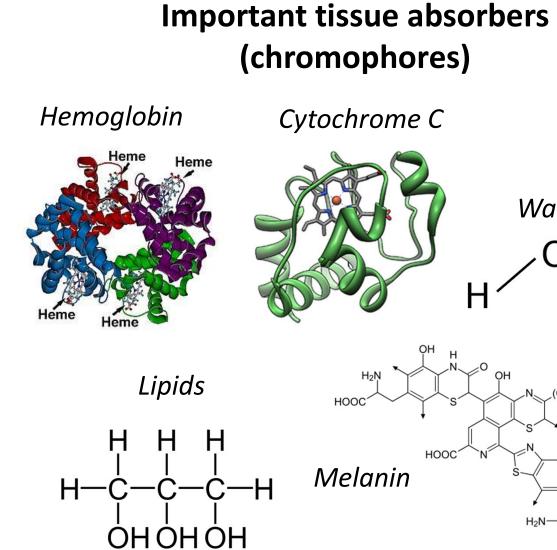
ELECTRONIC AND VIBRATIONAL



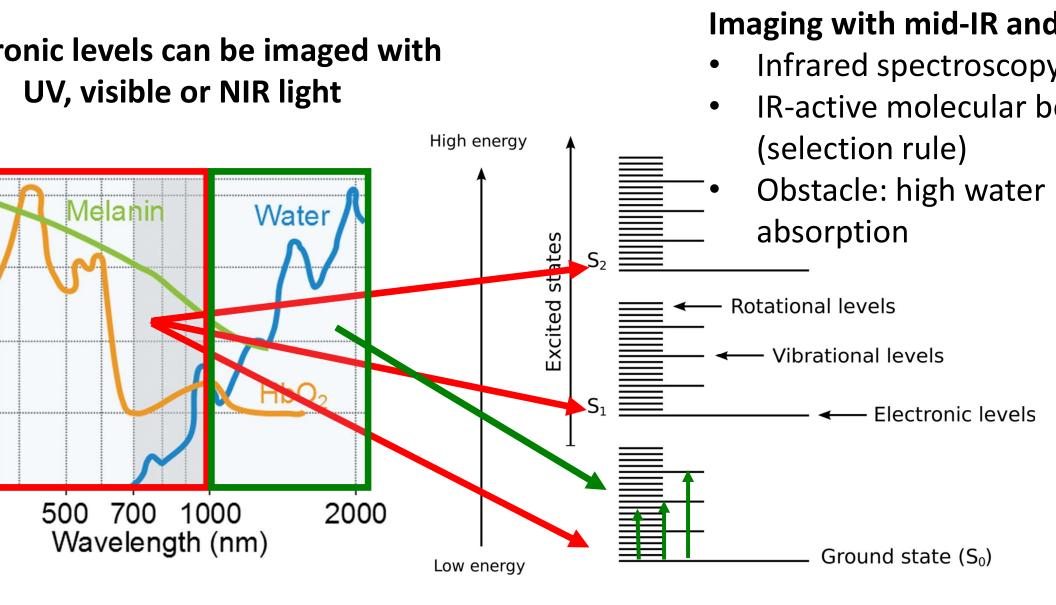
ABSORPTION SPECTRA OF COMPLEX MOLECULES : RESONANT PHENOMENON

Molecules have non-discrete excitation bands

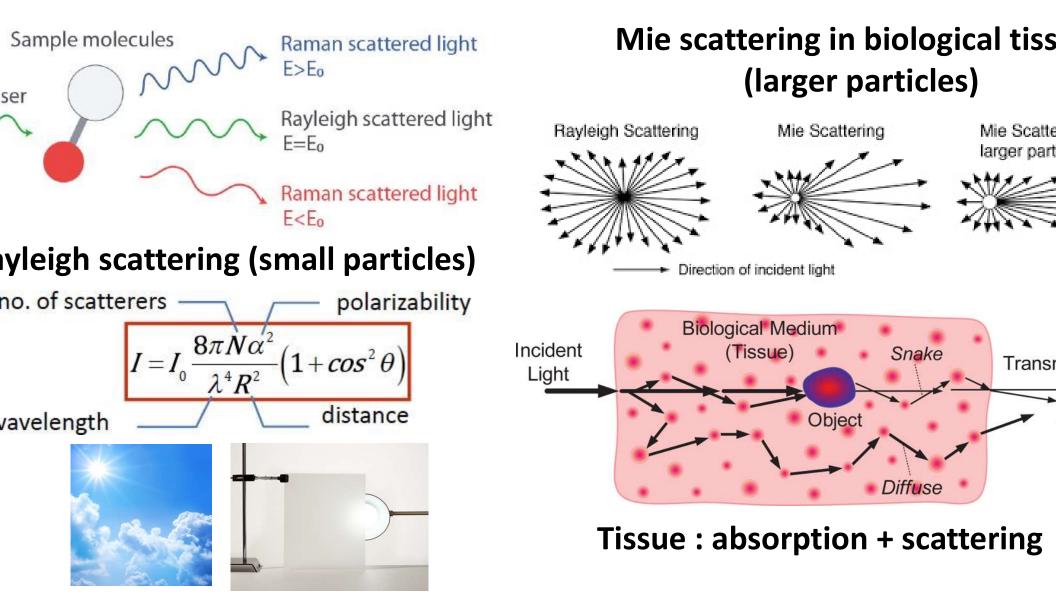




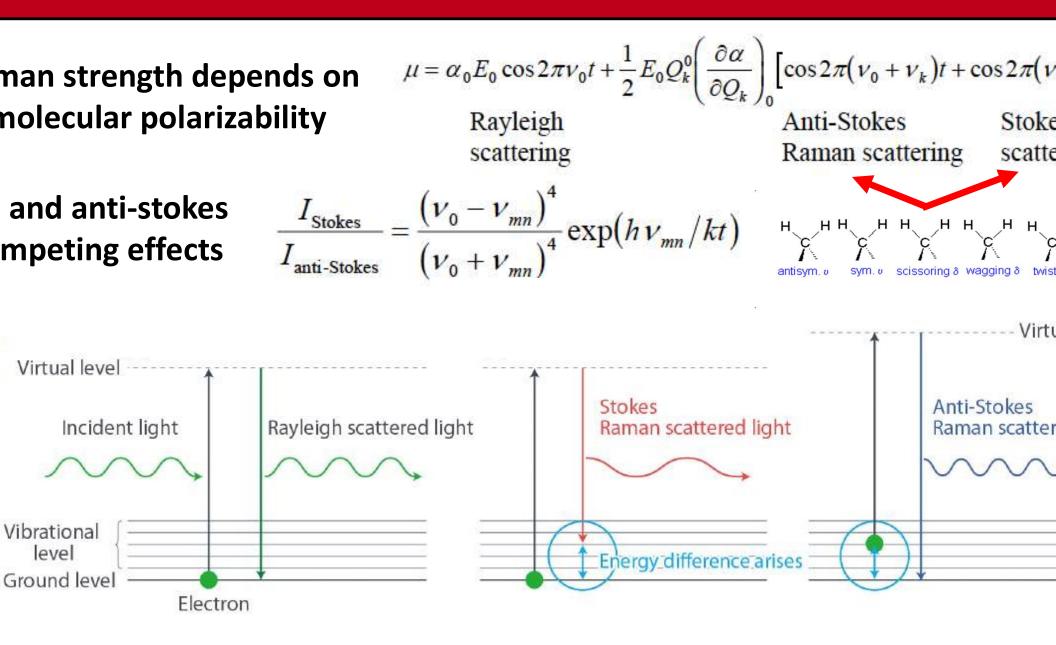
ABSORPTION AND VIBRATION MODES OF COMPLEX MOLECULES : RESONANT



NON-RESONANT PHOTON-ELECTRON INTERACTIONS : SCATTERING

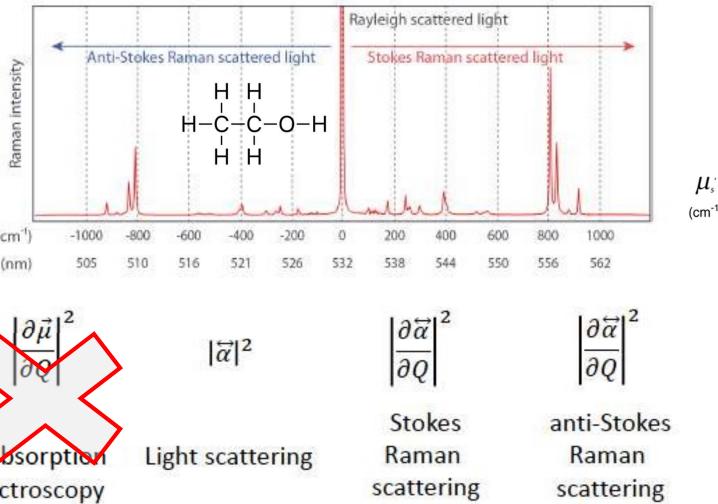


NON-RESONANT SPONTANEOUS RAMAN SCATTERING

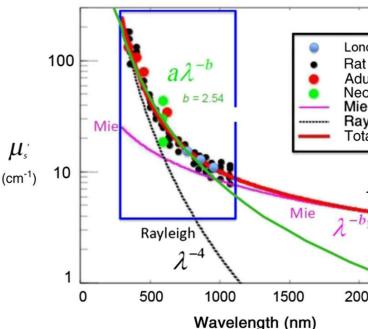


NON-RESONANT EXCITATIONS : SCATTERING IN TISSUE

Stokes and anti-stokes



Rayleigh/Mie scatte



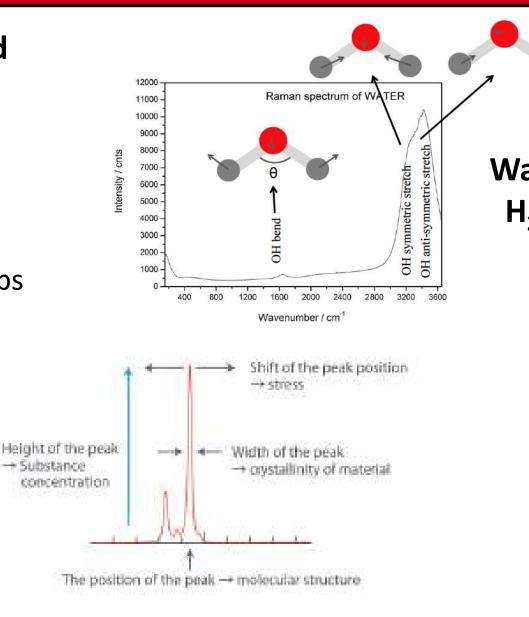
RAMAN SPECTROSCOPY : BIOCHEMICAL INTERPRETATION

ach vibrational mode can be modeled as a (an-)harmonic oscillator

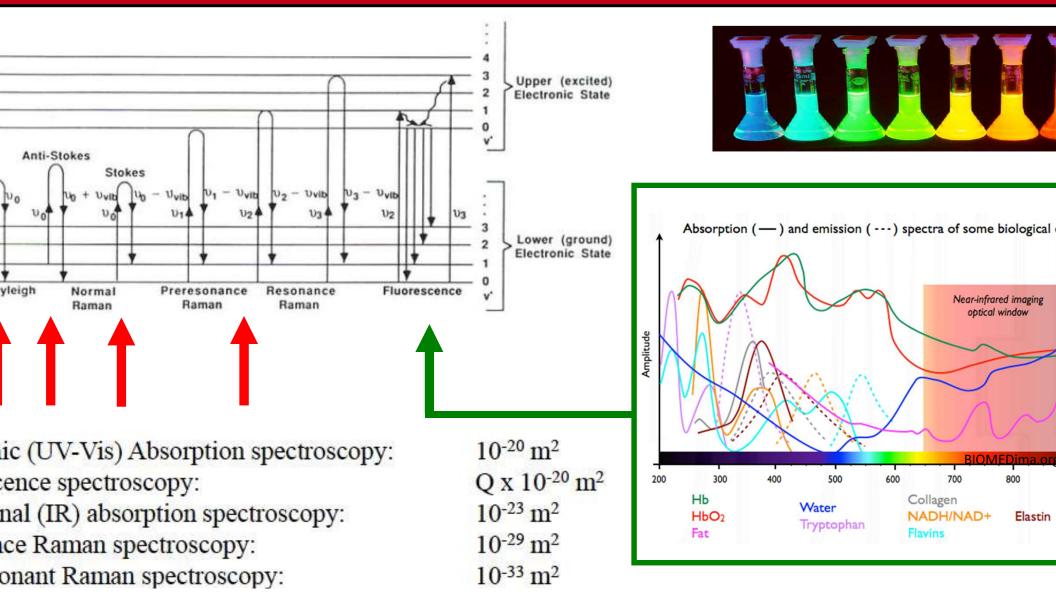
$$\sum_{m2}^{k} \frac{1}{\mu} = \frac{1}{m_1} + \frac{1}{m_2} \quad \upsilon = \frac{1}{2\pi} \sqrt{\frac{k}{\mu}}$$

Frequencies : unique for molecular groups Light atoms : larger frequencies Stronger bonds : larger frequencies

Peak **shift** : pressure applied Peak **width** : symmetry Peak **height** : concentration Peak **position** : molecular structure



ENDOGENOUS FLUORESCENCE : ANOTHERLIGHT-TISSUE NTERACTION COMPETING MECHANISM



- DATA MINING AND TISSUE CLASSIFICATION

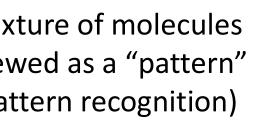


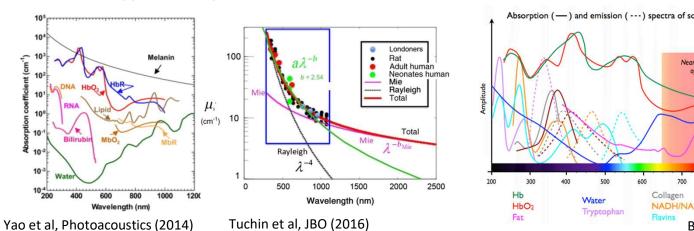




WHY ARE MULTIVARATE ANALYSIS USEFUL IN SPECTROSCOPY?

sue spectra (Raman, fuse reflectance, orescence) contain mplex biochemical ormation

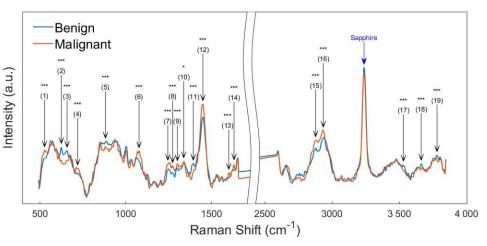




Fluorescend

700

Diffuse reflectance

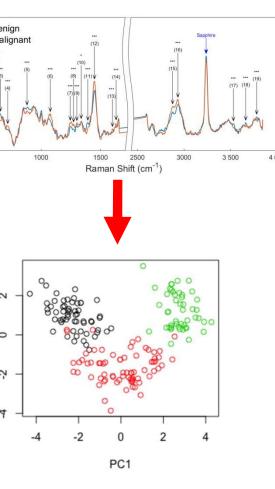


Vibrational spectroscopy

ACHINE LEARNING IN SPECTROSCOPY

Features selection

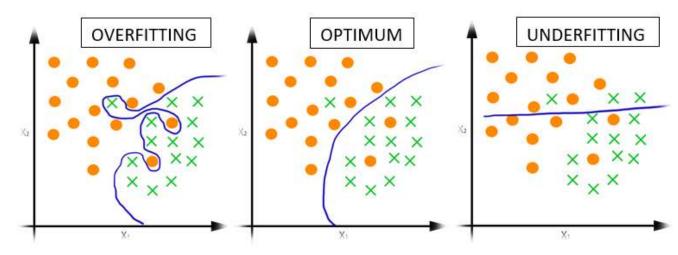
ect N-dimensional data on M-dimensional space)



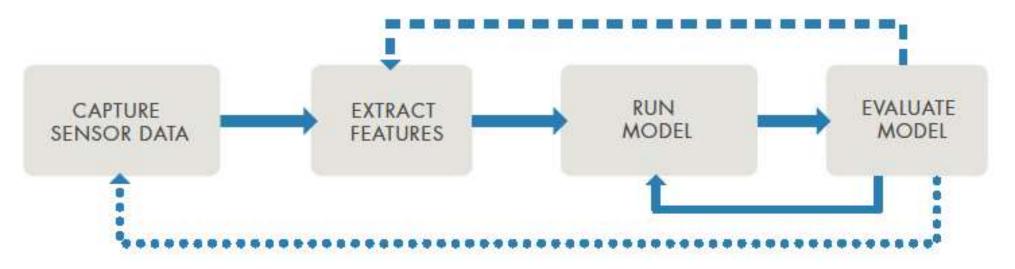
- Methods that can automatically detect patterns i data
- Uses uncovered patterns to predict future data, on to perform other kinds of decision making under uncertainty

Supervised learning and model building

- each measurement is assigned a label
- logistic regression, singular vector machine

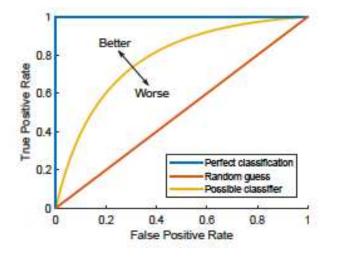


TERATIVE MACHINE LEARNING PROCESS



ceiver operating characteristic curve

false/true positives and negatives)



- Find classification model with no over-fitting
- Evaluate performance on an independent (hold-out) dataset : ROC curve

- BIOMEDICAL APPLICATIONS





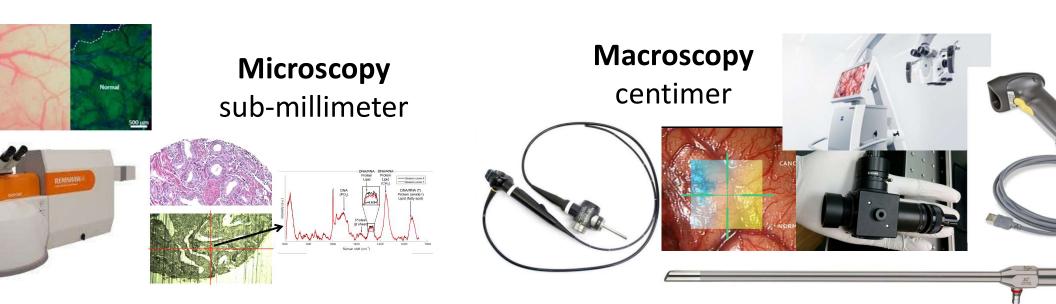


OPTICAL SPECTROSCOPY APPLICATIONS IN MEDICINE

Treatment	Monitoring treatment response and disease progression
<i>In situ</i> disease stratification to inform treatment decision making	Prognostication to better strat disease and provide tailored treatment
Guidance for surgical resection margin assessment/localization local drug administration focal therapy (<i>e.g.</i> brachytherapy)	Monitor disease progression, assess outcomes, and flag resid disease
Optics-enabled treatment using photochemical, photothermal, or photomechanical interactions to treat disease	Monitor treatment safety, especially for chronic condition and long-term treatments
	In situ disease stratification to inform treatment decision making Guidance for surgical resection margin assessment/localization local drug administration focal therapy (<i>e.g.</i> brachytherapy) Optics-enabled treatment using photochemical, photothermal, or photomechanical interactions to

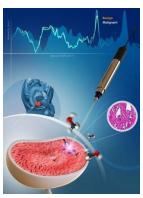
PLATFORM TECHNOLOGY : SPATIAL SCALES

Probing tissue structure from microscopic to macroscopic scales



Mesoscopy millimeter

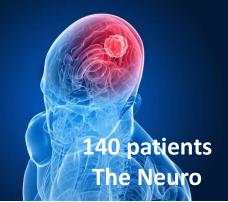




PLATFORM TECHNOLOGY : FINDING THE RIGHT APPLICATIONS

Designing statistic models across organ sites and diseases

Brain cancer



Epilepsy



Prostate cancer



Lung cancer





Gynecologic cancers





CASE STUDY - PROSTATE CANCER DETECTION STEP 1 : STUDY DESIGN

f patients	32
QR) age at RP, years	62 (58-66)
QR) preoperative PSA, μg/L Fs, n (%)	6.79 (5.33-8.50)
	4 (12)
	13 (41)
	7 (22)
	5 (16)
	3 (9)
ı (%)	
	0 (0)
	18 (56)
	9 (28)
	2 (6)
	3 (9)
al tumour stage, n (%)	
gan-confined)	13 (41)
xtra-prostatic extension)	15 (47)
eminal vesicle invasion)	4 (12)
of positive surgical margin, n (%)	10 (31)

e Group; IQR, interquartile range; RP, radical prostatectomy.

ournal of Urology (2018)

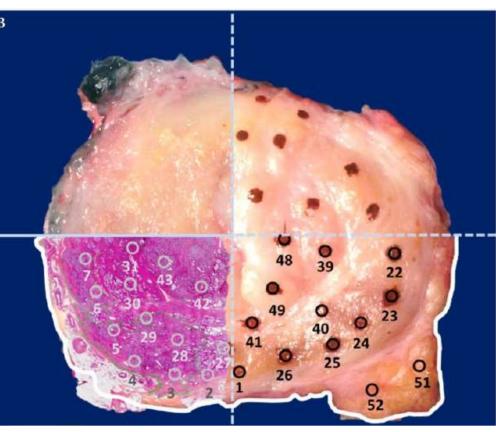
Objective – To improve safety and accuracy of prostatectomy proced

- Can spectroscopy detect cancel in a highly heterogeneous background of normal tissue?
- Can spectroscopy distinguish prostate from extra-prostate tis

Clinical and pathologic characteristics of paties with prostate cancer incluin the study

CASE STUDY - PROSTATE CANCER DETECTION STEP 2 : MEASUREMENTS



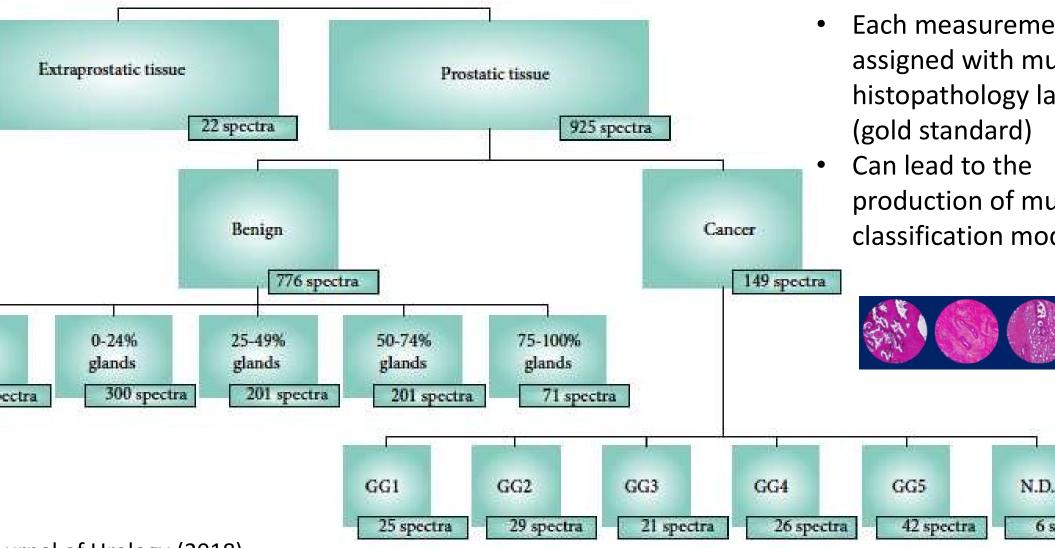


Intraoperative F probe syste

- real-time (0
 - 500 micro diameter sar
 - contact m

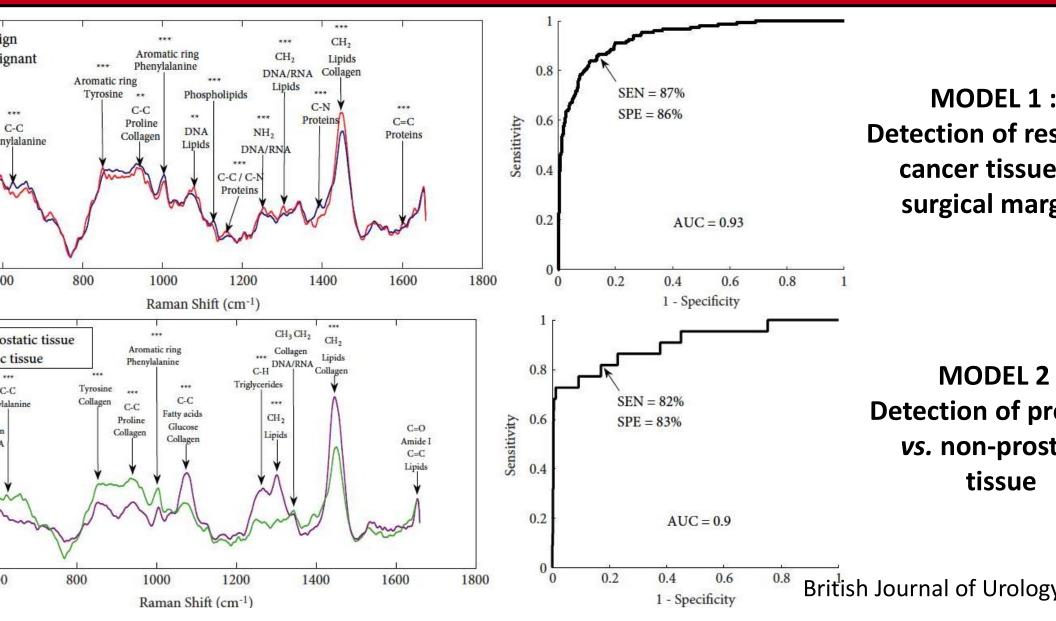
British Journal of Urology (2018

CASE STUDY - PROSTATE CANCER DETECTION STEP 3 : LABEL ASSIGNMENT



ournal of Urology (2018)

CASE STUDY - PROSTATE CANCER DETECTION STEP 4 : MACHINE LEARNING MODELS



CASE STUDY - PROSTATE CANCER DETECTION OPTIONAL STEP : BIOCHEMICAL INTERPRETATION

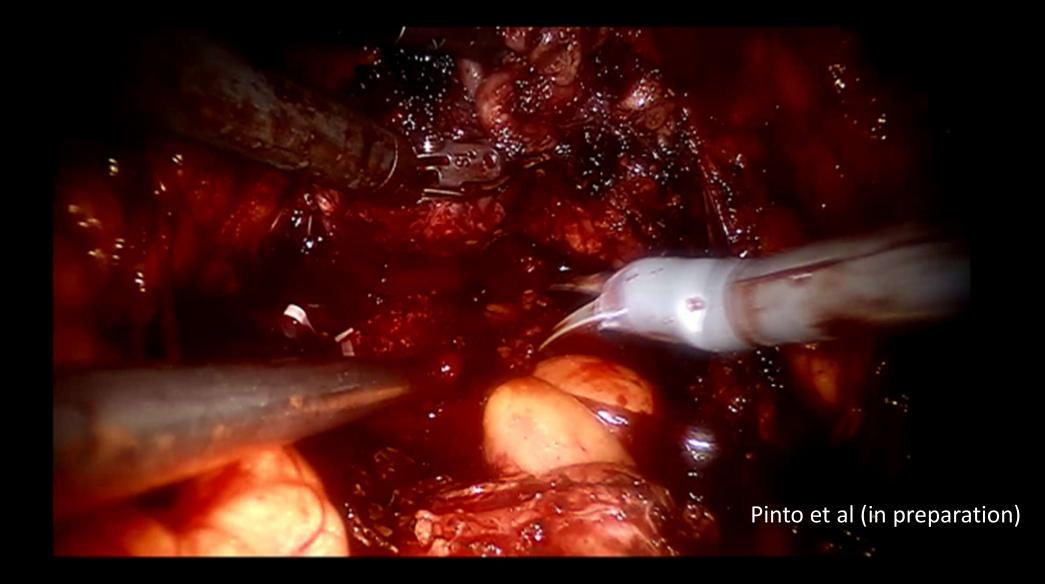
Tissue classes	Band centre, cm ⁻¹	Molecular bond assignment	Dominant class	Molecular species	Specific molecules	P
Extraprostatic/	573	C-S	Prostatic	Nucleic acids and proteins	DNA/RNA, Tryptophan	<0.001***
prostatic	625	C-C	Extraprostatic	Proteins	Phenylalanine	< 0.001***
.*	856	C-C	Prostatic	Proteins	Collagen, Tyrosine	< 0.001***
	940	C-C	Prostatic	Proteins	Collagen, Proline	< 0.001***
	1 004	0	Prostatic	Proteins	Phenylalanine (breathing)	< 0.001***
	1 074	Č-C	Extraprostatic	Lipids, Proteins, Carbohydrates	Fatty acids, Collagen, Glucose	< 0.001***
	1 267	C-H	Extraprostatic	Lipids	Triglycerides	< 0.001***
	1 302	CH ₂	Extraprostatic	Lipids	Methylene	< 0.001***
	1 342	CH ₃ CH ₂	N/A	Proteins and nucleic acids	Collagen, DNA/RNA	0.12 ^{NS}
	1 448	CH ₂	Extraprostatic	Lipids and proteins	Collagen	< 0.001***
	1 654	C=O/C=C	N/A	Proteins and lipids	Amide I, lipid chains	0.82 ^{NS}
Benign/	625	C-C	Benign	Proteins	Phenylalanine	< 0.001***
malignant	850		Malignant	Proteins	Tyrosine (Aromatic ring)	< 0.001***
	935	C-C	Benign	Proteins	Collagen, Proline	0.01**
	1 004		Benign	Proteins	Phenylalanine	< 0.001***
	1 077	C-C/C-O/PO2	Malignant	Nucleic acids and lipids	DNA	0.004**
	1 1 27	C-N	Benign	Phospholipids	Biological membranes	< 0.001***
	1 160	C-C/C-N	Malignant	Proteins	0	0.001**
	1 254	NH ₂	Malignant	Nucleic acids	DNA/RNA	< 0.001***
	1 303	CH,	Malignant	Nucleic acids and lipids	DNA/RNA	< 0.001***
	1 394	C-N	Benign	Proteins		< 0.001***
	1 448	CH ₂	Malignant	Proteins and lipids	Collagen	< 0.001***
	1 602	C=C	Malignant	Proteins	Phenylalanine	< 0.001***
GG 1/GG5	655	0-C=0	GGI	Proteins	Histidine	0.001***
	850	C-O-C	N/A	Carbohydrates	Polysaccharides	0.16 ^{NS}
	900	C-O-C	N/A	Carbohydrates	Monosaccharides	0.061 ^{NS}
	1 1 56	C-C/C-N	N/A	Proteins		0.008**
	1 256	Amide III	GG5	Nucleic acids and proteins	DNA/RNA, Amide III	< 0.001***
	1 448	CH ₂	N/A	Lipids and proteins	Collagen	0.79 NS
	1 517	C-C/C=C	GG1	Lipids	Carotenoids	< 0.001***
	1 604	C=C/	GG5	Proteins	Phenylalanine, Cytosine, Tyrosine	0.001**
	1 654	C=C/C=O	GGI	Lipids and proteins	Lipid chains and Amide I	0.001**

Univariate analyses of prominent Raman peaks identified by arrows in Figs 3–5A. GG, Grade Group. ***P < 0.001, *P < 0.05 and NS, non-significant (P > 0.05). References for band centre, molecular bond assignment and potential molecules for specific peaks are provided in the reference list [17,28–37].

CASE STUDY - PROSTATE CANCER DETECTION STEP 6 : INTEGRATION IN SURGICAL WORKFLOW



CASE STUDY - PROSTATE CANCER DETECTION STEP 6 : INTEGRATION IN SURGICAL WORKFLOW

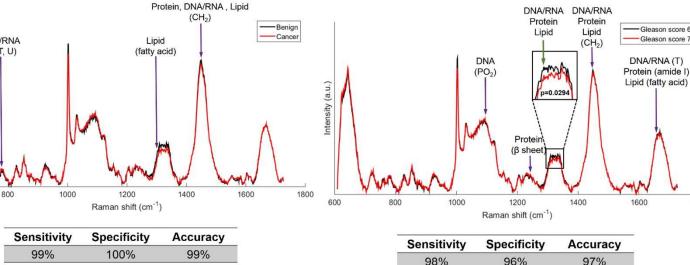


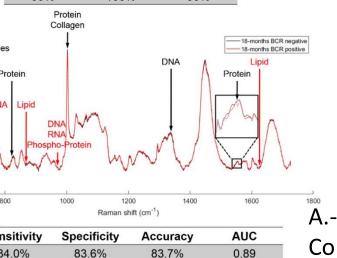
PROBING TISSUE AT MICROSCOPIC SCALES : PATHOLOGY APPLICATIONS IN PROSTATE CANCER

Stratification:

Gleason 6 vs 7

Diagnosis: Normal vs Cancer





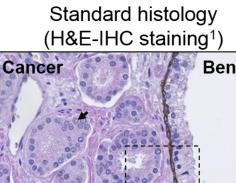
Prognosis: Biochemical recurrence (18 months)

A.-A. Grosset, *publications in preparation* Collaboration with Dr. Trudel's lab at CRCHUM

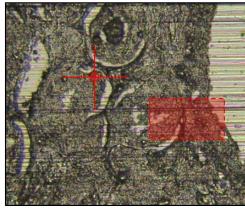
1800

Stained slides mappe

local Raman measure



Targeted location for measurement



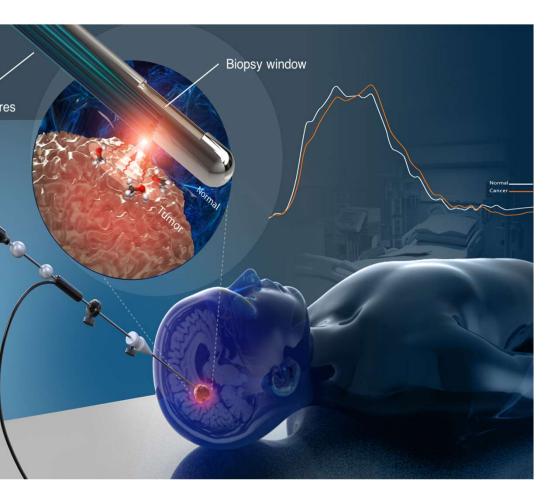
– INTRAOPERATIVE RAMAN DETECTION SYSTEMS AND SPECTS OF CLINICAL TRANSLATION





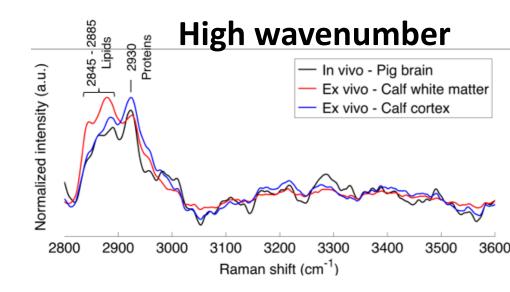


OPTICAL SPECTROSCOPY FOR TARGETED AND REAL TIME *IN SITU* TISSUE BIOPSY



fic Reports (2018)

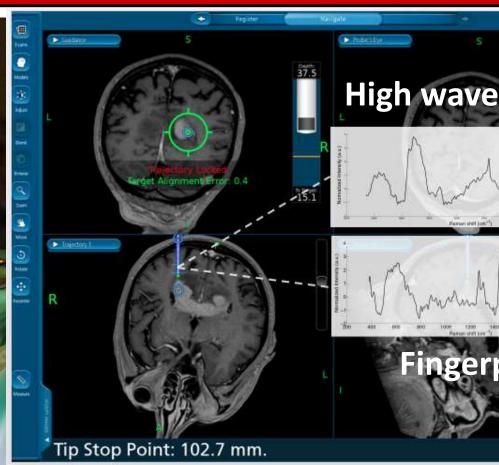




NTRAOPERATIVE FIBEROPTICS SYSTEM INTEGRATED

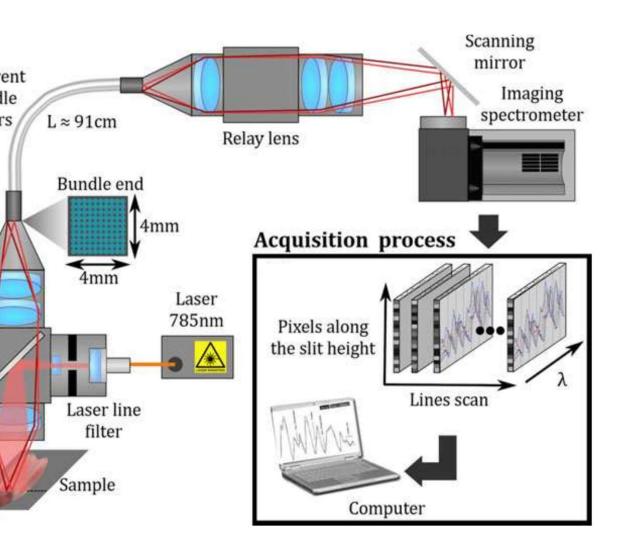
ruption to clinical low: 5 s acquisition nples spatially sistered with optical

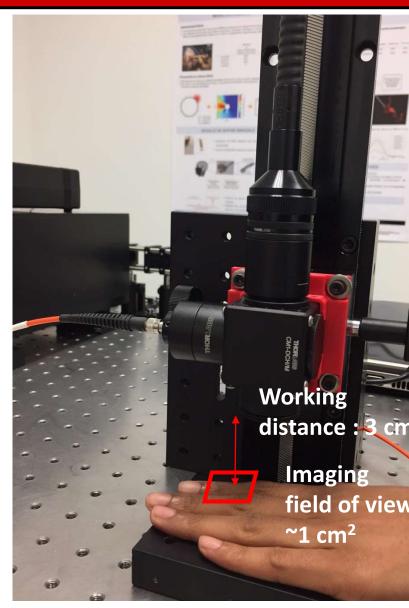
ta



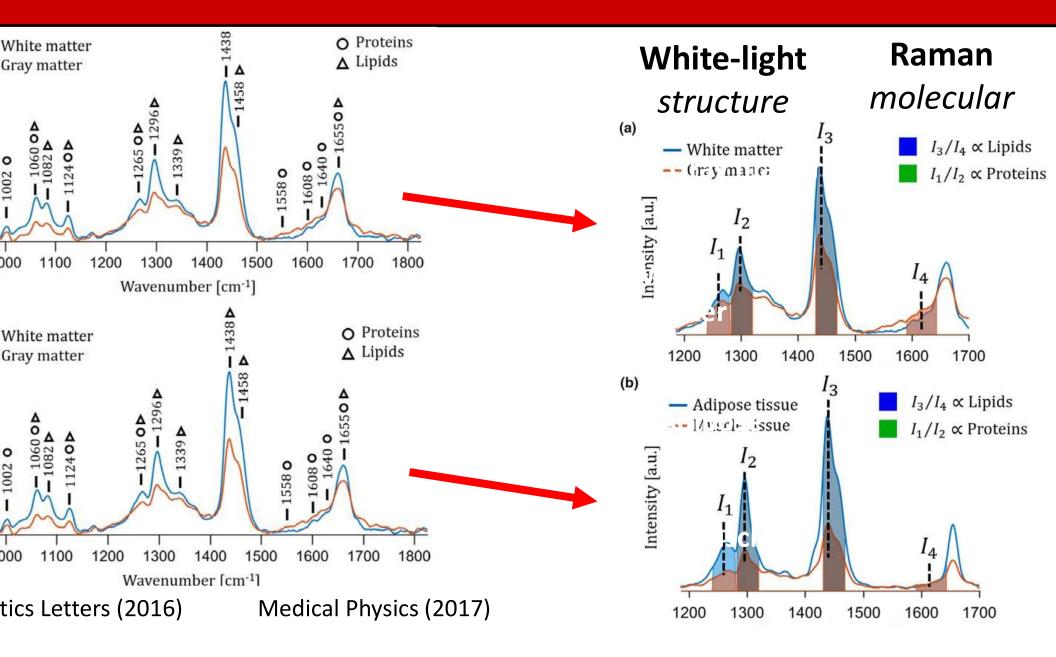
Desroches et al (in pre

WIDE-FIELD LINE-SCANNING RAMAN SPECTROSCOPY SYSTEM

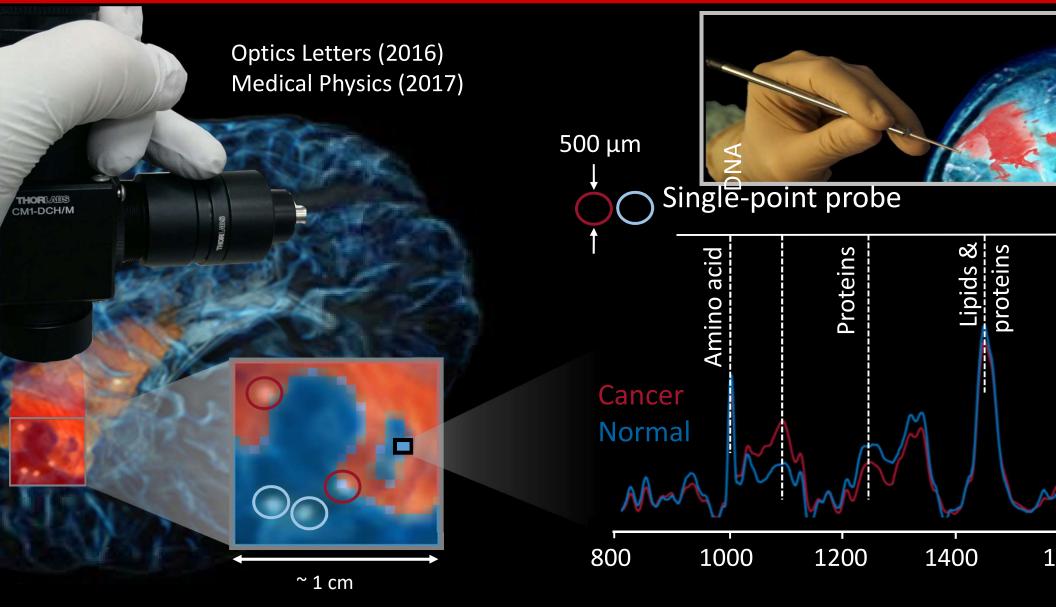




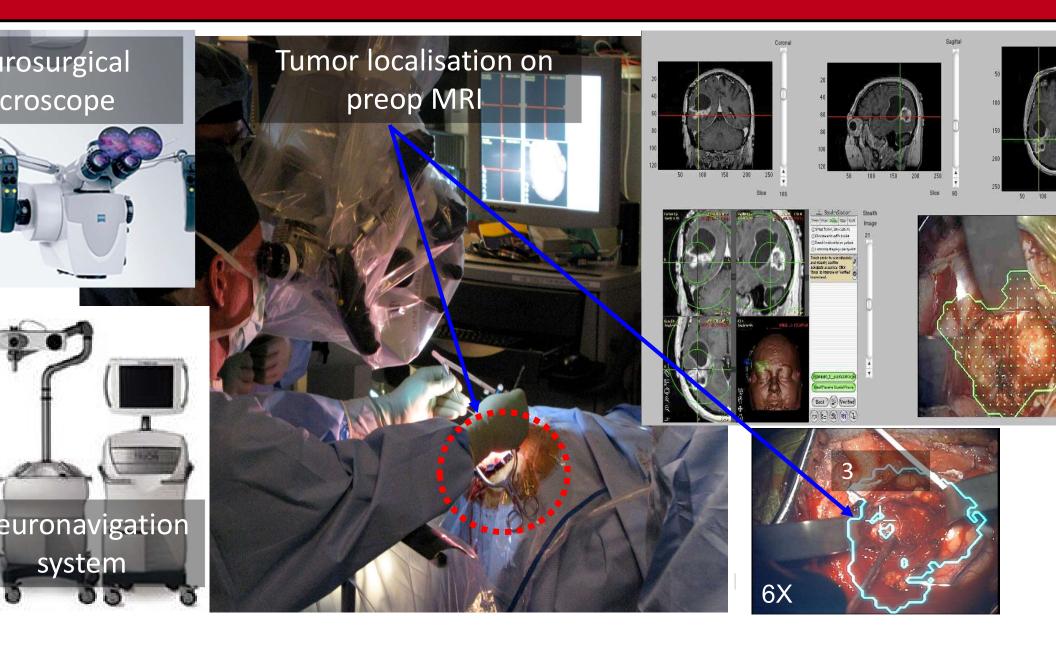
EATURES EXTRACTION AND TISSUE CLASSIFICATION



SPATIAL RESOLUTION MATCHES PROBE SYSTEM FOR PIXELIZED TISSUE CLASSIFICATION

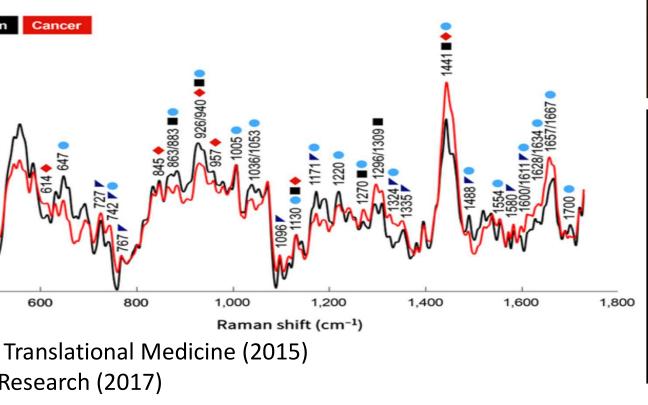


RESECTING TISSUE IN THE BRAIN : HOW-TO GUIDE

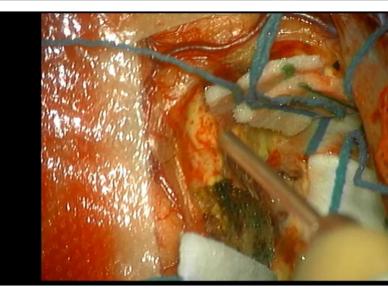


TUMOR RESECTION GUIDANCE IN BRAIN : RETROSPECTIVE CLINICAL STUDIES

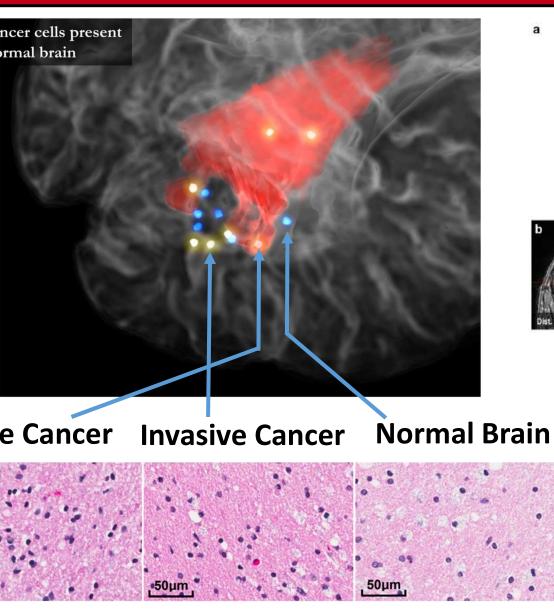
- an probe used *in vivo* for >**140 brain cancer nts** at the Neuro since 2013
- cancer detection sensitivity & specificity ding invasions **up to 2 cm beyond MRI contrast**

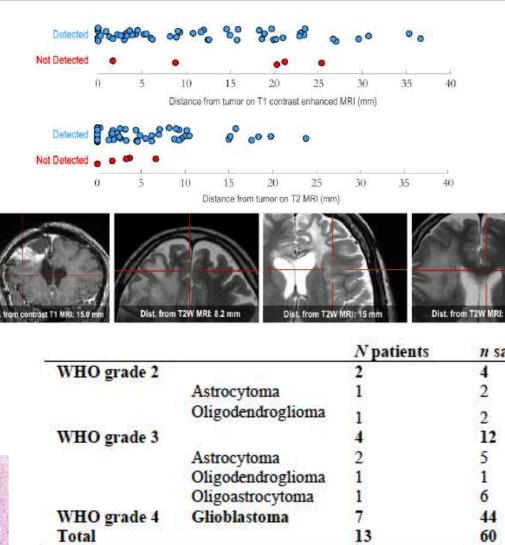






RAMAN SPECTROSCOPY DETECTS CANCER 2-3 CM BEYOND MRI ENHANCEMENT





Biomedical Optics Express (2016)

ANDOMISED CONTROL TRIAL AT THE NEURO



- Recruitement of 32 glioma patients (grade 2-4)
- Only first time surgeries
- Randomization at the end of the regular procedure
- Probe and live ODS classifier used for 50% of patie
- Tissue interrogation (cancer vs. normal) in **<1s**
- Clinical metrics: post-MRI contrast, weight of extra resected tissue, survival

Preliminary results:

- 25 patients completed
- Extra tissue resected in 40% of cases
- Live classifier achieves 85% specificity

CLINICAL TRANSLATION OF A RAMAN SURGICAL TOOL : PROBLEMS AND SOLUTIONS

	Ideal solution(s)		Practical solution(s)
nodel performance consistency with training dataset tissue sampling cy with pathology in statistical modeling	 Automated laser exposure/imaging time routines for SNR optimization Minimize tissue background signal (<i>e.g.</i> AF photobleaching) Ensure Raman SNR consistent with training dataset Ensure training dataset captures full normal/benign/cancer tissue heterogeneit Feature selection optimized with independent dataset Spatial registration with histopathology and sufficiently detailed reports 		
hting specific NIR contributions filter bleed-through	Turn-off all light sourcesOnly an issue for open surgical procedures	al	 Device-triggered light shut dow Physical filtering of all light sour make OR optical device friendly
onse variability and scalability variations between study patients I centers	 Detailed calibration procedure (x-axis, NIST standard, laser power monitoring) Implement at several time points including before and after sterilization Monitor changes to ensure data consistency 		
ng in surgical cavity uation from absorption mination from blood Raman	 Ensure surgical cavity is clean prior to measurement Possible in neurosurgery, likely unrealistic for several other applications 	 Pressure applied with probe leaves negligible blood Classification models emphasizing only featu minimally affected by blood Signal rejection based on presence of blood 	
nstrument depth sensitivity	Biophysical model for each instrument to evaluate system performance and predict under various tissue conditions		

– OTHER INTRAOPERATIVE IMAGING SYSTEMS : _UORESCENCE AND DIFFUSE REFLECTANCE

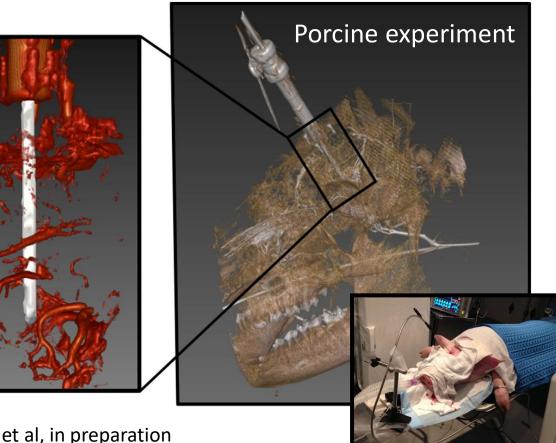


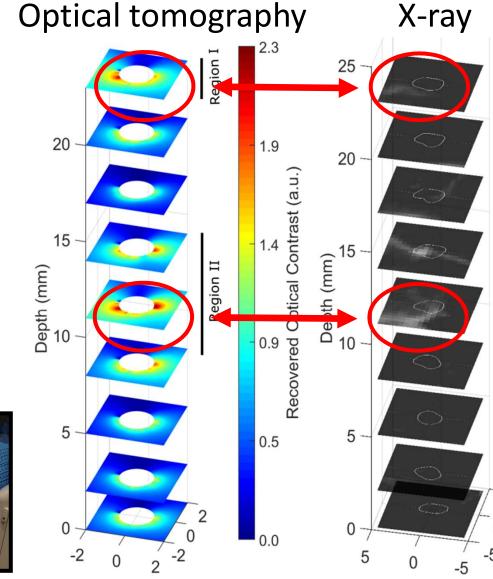




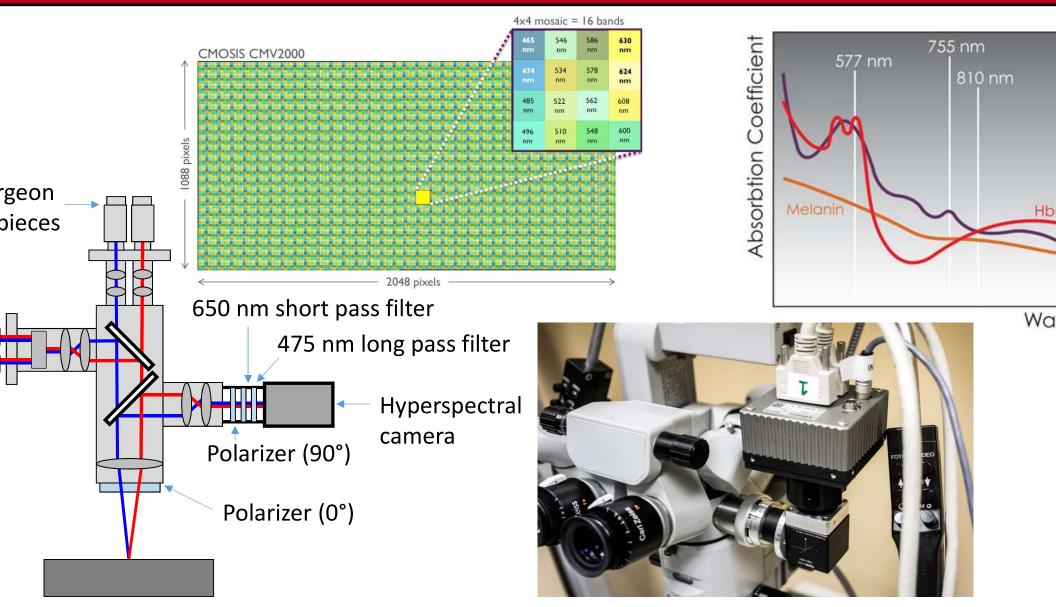
REDUCING HEMORRHAGE RISK DURING BIOPSY SAMPLE HARVESTING

angiography as gold-standard for vessels detection

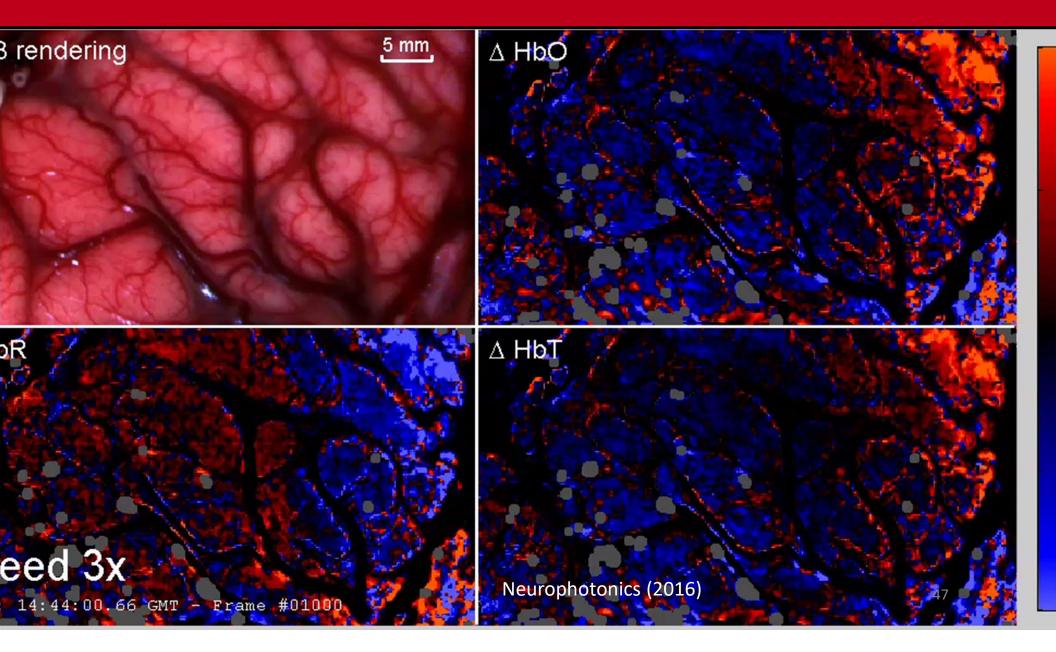




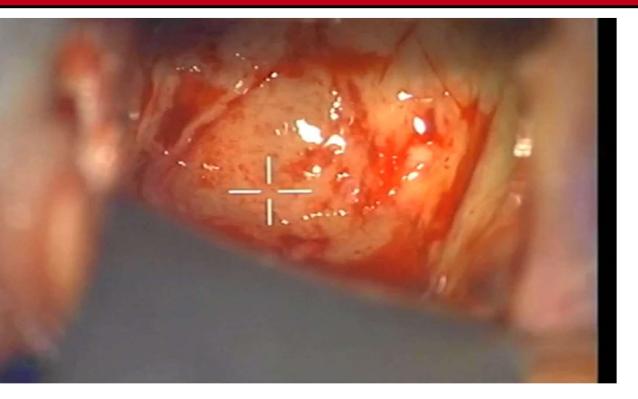
NTRAOPERATIVE HYPERSPECTRAL REFLECTANCE IMAGING

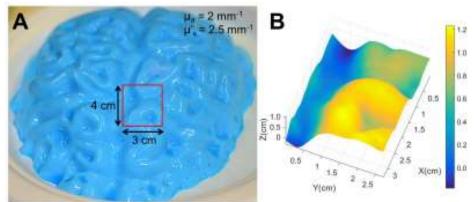


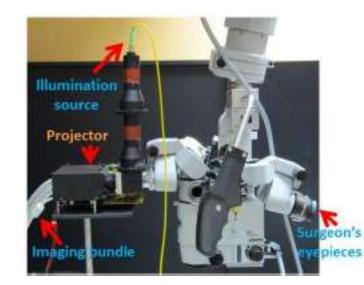
HEMODYNAMIC RESPONSE IMAGING

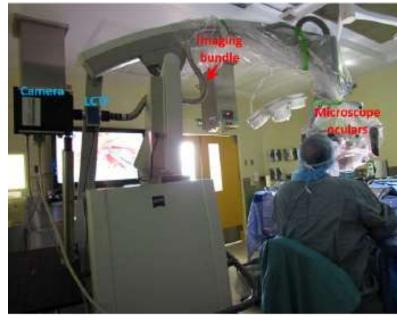


LUORESCENCE-GUIDED SURGERY

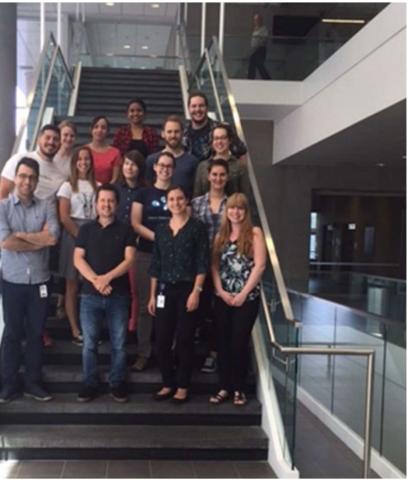








URRENT RESEARCH GROUP MEMBERS ND COLLABORATORS



POLYTECHNIQUE MONTRÉAL





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